INTEGRATING AGILE COMBAT SUPPORT WITHIN TITLE 10 WARGAMES

THESIS

Daniel A. Krievs, Captain, USAF

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DEPARTMENT OF THE AIR FORCE
AIR UNIVERSITY

AIR FORCE INSTITUTE OF TECHNOLOGY

Wright-Patterson Air Force Base, Ohio

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Daniel A. Krievs, BS

Captain, USAF

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Daniel A. Krievs, BS

Captain, USAF

Committee Membership:

Dr. J.O. Miller
Chair

Dr. D.K. Ahner
Member

AFIT-ENS-MS-15-M-127

Abstract

Air Force (AF) Concept Development and Experimentation (CD&E) continually progresses the evolution of AF while achieving national security and military objectives. CD&E experiments on future challenges, procurement of new weapon systems and tests existing/innovative strategies as potential solutions. The primary tool that CD&E utilizes in conducting these experiments is wargaming. This thesis provides a foundation to incorporate logistics into Air Force Title 10 wargames. More specifically, we capture Air Force Materiel Command's (AFMC) Agile Combat Support (ACS) within an unclassified general wargame scenario. Logistics has been omitted from wargames for a multitude of reasons throughout the years. We develop a logistics simulation model of a simplified wargame scenario designed to be run within the Logistics Composite Model (LCOM) Analysis Toolkit (ATK) version 4.0 before a wargame initiates. We capture ACS within the stochastic simulation by incorporating engine failures, maintenance crews, ammunition, fuel, and various other logistics metrics. By varying the types of sortie operations and the logistics support available, further insight is gathered on Blue Force capabilities. We develop decision quality information to present to a decision maker by combining statistical and multivariate analysis. Our approach showcases how to gather insights from ACS metrics, including development of a metamodel using only four metrics to successfully predict key ACS Measures of Effectiveness (MOEs). Ultimately, we design, analyze and demonstrate that logistics can and should be incorporated into wargames.

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To Mom and Dad

Acknowledgments

I would like to express my sincere appreciation to my faculty advisor, Dr. J.O. Miller, for his guidance and support throughout the course of this thesis effort. I would, also, like to thank Dr. D.K. Ahner, for his invaluable insight throughout our research.

Daniel A. Krievs

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INTEGRATING AGILE COMBAT SUPPORT WITHIN TITLE 10 WARGAMES

I. Introduction

This thesis provides an approach of capturing logistics within wargames. Wargaming has been used throughout the history of warfare to ensure battle commanders are prepared and informed of potential scenarios they might encounter. As time has progressed, the warfare has changed from tribal to medieval to trench to guerilla and now to modern warfare. As these types of warfare have evolved, the form of wargames has had to adapt ranging from table top discussion to combat model simulations. While the types of simulations used for wargames has adapted, there is still a typical flaw in omitting logistics from the models. The reasoning has been from a culmination of things, but the bottom line is with today's budgetary constraints, battle commanders must be cognizant of the supplies that they require to complete missions and maintain the United States Air Force's (USAF) dominance in air, space, and cyberspace.

Problem Statement

President Obama signed the "Priorities for the 21st Century Defense" on January 3, 2012. The memorandum states that there will be a rebalancing of US troops toward the Asia-Pacific region. Air Force Materiel Command (AFMC/A4&A8) then conducted a study to determine how the Air Force (AF) assesses its capabilities in future air campaigns. The results were astonishing because Agile Combat Support (ACS) is only accounted for 30 days into the future and are omitted from studies that assess long term armed conflicts such as wargames. These results were not pleasing and something needed to be done to fix the gap between wargames and logistics. This thesis effort is to

determine how ACS can be captured effectively and timely in Title 10 wargames. These wargames are referred to as Title 10 due to the service chiefs' responsibilities outlined in U.S. Code Title 10 to train their respective forces.

General Issue

Logistics has been continuously omitted from wargames for many reasons. Traditionally, logistics has been an afterthought because of the ability to continuously increase budgets to support armed conflicts. As time is progressing, the Department of Defense (DoD) budget is increasingly more constrained with a growing emphasis on accurately projecting the costs associated with future engagements. Wargaming has been the hallmark of US forces in determining how the US will overcome opponents. The outcomes of these wargames highly influence location of personnel/equipment, procurement of weapon systems, and defining the tactics needed to be successful; however, not incorporating logistics is a failure that needs to be addressed.

In recent years, computer simulations for wargames have been trying to capture logistics within their combat models. The simulations have failed time and time again for many reasons. One of the main issues of incorporating logistics into wargames is the conflicting aggregation levels of the models. Wargame combat models have primarily been used at the campaign level, while logistics simulation models have used a more detailed tactical level model without explicit modeling many combat operations.

Wargame combat models have stayed at the campaign level because of the following:

- Time saved by running a more aggregated model
- The focus of wargames being on opponent decision making

- Commanders being overwhelmed by data from a lower level model

Logistic models have been unable to run during wargames because of the short window of time to complete the model. Wargames are completed on 24 hour cycles, but this short period in time makes it difficult to capture reasonable logistic impacts.

Research Objectives/Questions/Hypotheses

The goal of this study is to answer the following questions:

1. What simulation platform is most appropriate for incorporating logistics into wargames?
2. At what point should the logistics simulation being completed within the wargame process?
3. Is there a logistics metamodel that can be adjusted and completed during wargames?
4. What metrics are the most vital and able to represent ACS?

Our goal is to produce a proof of concept logistics simulation within a wargame scenario to model the constraints and capabilities associated with ACS. The results from this simulation are then garnered to develop further limitations and constraints regarding the capabilities of US forces. We believe that the most ideal approach in capturing logistics within wargames is to complete a logistics simulation before the wargames begin and to capture key logistics outcomes in a metamodel. This provides wargame commanders with more realistic force capabilities including ACS during a wargame and an opportunity to adjust their strategies based on these updates.

Scope

This research responds to a question from AFMC/A4/A8 regarding a method to capture logistics effectively and timely in a wargame. The modeling of an enhanced or deployed logistics capability in support of a specific scenario needs to be broken down

into two subcomponents. One component being the delivery of initial parts and equipment to support ACS in the wargame carried out by Air Mobility Command (AMC). The other component is ACS logistic operations being conducted during the wargame handled by AFMC. The primary objective of our research is to identify feasible metrics to capture ACS within a wargame and to present these metrics as part of military decision making process.

This thesis focuses on the computer modeling of ACS in Title 10 wargames. We work under the confinements and goals associated with United Engagements (UE). We are not attempting to replace or construct a theory of war. Rather this thesis attempts to use the ideas of previous wargames and answer its basic question of how a strategic wargame can capture logistics.

Methodology

We first develop a mission statement for logistics being incorporated into wargames. This statement drives the analysis and determination along the course of the study. After this we move into understanding why logistics has been omitted from wargames. This cause leads into what type of simulation platform to utilize. We develop a fictional wargame scenario around this simulation model and develop a proof of concept. The analysis is partitioned into two cases. The first case analyzes the entire set of output data from the simulation to develop constraints, limitations, and provide a more accurate representation of the ACS capabilities and constraints for forces involved in the wargame. The second case revolves around the idea of developing a logistics metamodel

that can be run during an actual wargame. Both of these cases focus on the goal of incorporating logistics into wargames.

Summary

This thesis explores the realm of the relationship between logistics and wargames. We discuss why there has been a lack of importance to incorporate logistics and what issues arise when wargames attempt to bring in logistics. We focus specifically on ACS and develop a proof of concept that develops a further understanding of how to capture ACS capabilities and constraints for our forces included in the wargame. A combat mission doesn't just require a squadron of fighter jets; it also requires the personnel and equipment to support them. The next chapter of this thesis provides an overview of wargames and the lack of connection between logistics and wargames.

II. Literature Review

The purpose of this chapter is to review literature on wargames, the issues associated with incorporating logistics into wargames, Agile Combat Support (ACS), and the Logistics Composite (LCOM) simulation model. We begin the chapter by discussing the applications of wargames and how the USAF utilizes wargames. We then investigate the underlying issues with capturing logistics in wargames. Finally, we discuss how ACS is a part of AF logistics and why LCOM is the appropriate platform to complete a logistics model for a wargame.

Wargame Overview

Wargaming has been used throughout history as a fundamental tool in developing military strategy. These strategies have then been incorporated into training, education, procurement, and many other areas of the US military (Perla, 1990:3). The USAF defines wargames as "a simulation, by whatever means, of a military operation involving two or more opposing forces, using rules, data, and procedures designed to depict an actual or assumed real life situation" (McHugh and Fischer, 1966:9). The goal of wargames is ultimately communication (Perla, 1990:185). This communication showcases the cause and effect of wargame weapon systems interactions and the decisions made by the commanders.

This decision making is what sets apart a simulation from a wargame. Incorporating commanders as decision makers into wargame models allows for unique unrepeatable simulations. Thus wargames are not regarded as analytical tools (Long, 1993:5); however, this is the most essential part of wargames. The human in the loop

allows wargames to be unpredictable and deviate from the mundane rules and algorithms utilized by computer simulations. "Good wargames must be structured to help human players make decisions and allow them to learn about the effects of those decisions" (Perla, 1990:164). Ultimately, this human element of decision making is the key in providing the educational experience gathered from wargames.

The educational experience is the ability of wargames to allow commanders to test warfare strategy against enemy opponents without having loss of life. This asset increases the wargame commanders' knowledge of war and increases their decision making abilities. Wargames are able to achieve this because they use mathematical combat models to simulate the physical interactions between weapon systems (Perla, 1990:164). These models are developed to understand the Measures of Effectiveness (MOEs) of one weapon system against an enemy force. Wargame commanders then theorize and provide their decisions of force movement to the combat models. In addition, opposing commanders are using similar weapon systems and strategizing to achieve their missions at the other's expense. This becomes an issue in today's environment where USAF opponents are not at the same level of technology and the decisions that the opponents make are far different then gathered from the wargame. Models that can accurately capture the actual opponent's supply, weapon systems, and decision making provide far more insight then playing a wargame against ourselves.

Wargames have evolved overtime to minimize this issue of capturing an opponent's decision making by forcing opposing commanders to study and become familiar with enemy tactics (Perla, 1990:203). Their primary mission is to become knowledgeable in the enemy's culture to develop a mindset that is the foundation to their

judgment during wargames. Opposing commanders' expertise in their respective enemy culture provides the necessary realism against the friendly forces, but it fails to provide a justification as to why an enemy force moves to a particular location or engages in an attack. The issues that arise from here derive from the aggregation level of wargames.

Dr. C. L. Helwig brought the concept of aggregation to light back in 1780 when he "employed a single playing piece to represent a large body of soldiers" (Perla 1990:18). Wargames follow Dr. Helwig's idea by having their combat models operate at the strategic aggregation level. At this level, like forces are gathered together to form wings, battalions, etc. There isn't individual weapon system versus weapon system as in tactical combat models, but instead a large force opposing another large force. The inputs for the model are things to the effect of defeated army battalions and the outputs are surrendering. The strategic combat model then uses computer algorithms to convert these inputs into outputs by using mechanisms that are not only militaristic but political, psychological, diplomatic, etc. A great example as to why strategic combat models don't only include military operations (e.g. destroying infrastructure) is the recent war in Afghanistan. US forces have destroyed a large amount of infrastructure and controlled the land within the country in a short amount of time, yet the war continued for a decade. This example showcases how wars are not always symmetric and easily understood. Winning a war sometimes takes more than destroying enemy forces and that's a reason why wargames are conducted at the strategic level. Strategic combat models have the ability to incorporate symmetric and asymmetric effects. The downside is that there is a vast amount of assumptions when running at the strategic level. These assumptions take logistics for granted and assume that a forward operating base (FOB) maintains, operates,

and supports any mission used during the wargame. The example of the “War on Terror” in Afghanistan is a perfect reason why logistics shouldn’t be assumed. This type of war refocused from force on force attrition to prolonged forward sustainment. The questions changed from how well our airpower can compete against the enemy forces to questions like the following:

- What is the minimal amount of aircraft in the forward operating bases needed to maintain day to day operations?
- Can the USAF continue to fund weapon system upgrades while maintaining overseas operations?
- What is the cost/benefit of operating a FOB as opposed to long range weapon systems?

These are only a small snapshot of questions regarding strategic level AF leaders, and as with the past, wargames are the likely tool to provide insights on these questions. The ongoing evolution of wargames must continue and have the ability to include the effects of logistics. Incorporating logistics will more accurately represent the forces involved in wargames, but more importantly, allow wargames to be even better tools for answering questions in today’s world.

USAF Wargames

Wargames are used within several levels of the Air Force. Each level provides different types of insight, but we concentrate on Title 10 wargames. “As the Goldwater-Nichols Act of 1986 gave the service chiefs responsibility under U.S. Code Title 10 to train, man, and equip their individual forces” (Ducharme, 2012:1). The Air Force began conducting Title 10 wargames in 1995 by creating two types of wargames: Unified Engagement (UE) and Future Capabilities Game (Ducharme, 2012:2). UE wargames are completed on even years with Future Capabilities Games being held on odd years. These

two types of wargames have entirely different objectives, but we strictly focus on Unified Engagements.

The goal of UE is to "address military challenges and concept exploration" within the Pacific and European theaters (Ducharme, 2012:2). The wargames are conducted in theater and are based on technologies that are near term (approximately 12 years out). UE is established to be a tool that an operational Commander can use to develop and test campaign level strategies in their respective theater (Ducharme, 2012:43). There are three teams or forces involved with the wargames. The white team adjudicates; the Blue Force represents the US forces while the Red Force represents the enemy forces (Caffrey, 2008:40). The players during these wargames are the decision makers and are using history, culture, and doctrine to develop strategies and crisis action plans (Caffrey, 2008:43). Each UE is different and the rules for winning the wargame change; however, the main goal is not necessarily to win the wargame but to come out with useful insights on operational strategies (Haffa, 2001). Because of the complexity of typical UE scenarios, constructive computer simulations are used to capture daily Red and Blue Force moves as well as adjudication of battlefield engagements.

Logistics in Wargames

There is no definitive date in which wargames were created. It is due to the fact that wargames have been executed throughout the history of mankind. The definitions vary but the heart of each definition remains the same. Wargames are fictional studies carried out by military leaders to construct, amend and/or validate a war plan (Collins, 2012). There are various forms of wargames that are also carried out by the commercial

industry; however, we focus on US Air Force wargames and understand the role that logistics has played in wargames. This section illustrates the shortcomings that logistics has had in wargames and the numerous issues involved with these shortcomings.

One of the key issues of UE is a failure to evaluate the logistic operations (Haffa, 2001). Logistics is regarded as an operational constraint and fails to incorporate the "logistic support effects on campaign planning" (LaPlante et al., 1996:97). Blue Forces overestimate their effectiveness level and completely disregard the logistics involved in supporting their campaign. For example, the kill rates included in the simulations require that munitions be provided for each of the weapon systems; however, the amount of ammunition available is considered unlimited and use is not tracked (Haffa 2001). This in turn over predicts the effectiveness of US forces, under predicts the red forces, underestimates the budget and provides less insightful results to a large number of policies and doctrine (Caffrey, 2008:37).

Other reasons that logistics has failed to be captured in wargames are because logisticians/warfighters were excluded from the wargames (LaPlante, 1996:97) and the cost/complexity of incorporating logistics is far too great (Ducharme, 2012:4). Over the last couple of decades logisticians and warfighters have been incorporated into wargames; however, there were still issues in capturing logistics in simulation models (LaPlante, 1996:97).

The main reason for this matter was still the issues with complexity and cost of further developing the wargame models; but funding a project to develop and maintain logistics within a wargame simulation model is far less expensive than underestimating the budget for a war in the Pacific.

Agile Combat Support (ACS)

Logistics impacts every facet of the Air Force. From the delivery of F-35s to helmets delivered to Airmen, logistics plays a role. The AF breaks logistics into two commands: Air Mobility Command (AMC) and Air Force Materiel Command (AFMC). This paper focuses on the AFMC piece. AFMC provides logistics by executing Agile Combat Support (ACS). "ACS is the ability to create, protect, and sustain air and space forces across the full range of military operations" (Westhauser, 2011:1). It is the Air Force's capability that is responsible for determining what is deployed and how it will arrive and return to CONUS safely.

The Air Force Doctrine Document 4-0 Combat Support defines ACS using the following attributes:

- Agility: ensuring timely deployment concentration, adaptive employment and resourceful sustainment of air and space power (Westhauser, 2011:1).
- Reliability: competency and health of personnel, dependability of equipment, and trustworthiness of information (Westhauser, 2011:2).
- Integration: incorporate diverse parts into a common team to create a synergistic effect (Westhauser, 2011:2).
- Responsiveness: ACS capabilities are the right size, correct time and location (Westhauser, 2011:2).

ACS effects are measured by readied forces, prepared battlespace, positioned forces, employed forces, sustained forces, and recovered forces (Westhauser, 2011:3). These metrics are ultimately provided to the Commander Air Force Forces (COMAFFOR). ACS then uses its master processes to apply the attributes and produce the desired effects set forth by the COMAFFOR. ACS maintains, supplies, and distributes at "operating locations to achieve the mission and assure the operational utility of all personnel, materiel, equipment, and the operating location infrastructure"

(Westhauser, 2011:6). The services that ACS provides include lodging, medical, religious, postal, maintenance, and many others (Westhauser, 2011:7).

ACS is a part of every AF functional area and is a vital component in the Air Force's mission to train, equip, and employ air and space power. Omitting their role during wargames by assumptions is not a good practice.

Logistics Composite (LCOM) Simulation Model

The purpose of this section is to provide the readers with what the Logistics Composite (LCOM) simulation model is and why we feel that this is an appropriate model to use for our wargame.

LCOM is a discrete event simulation that uses distributions and random number generators to capture maintenance and optimize manpower levels (Cole, 2007). The LCOM model is a composite of modules, written in SIMSCRIPT II, which communicate with each other to function as a cohesive entity (AFLCMC/EZJS, 2013). The three modules are: the Input Module that preprocesses the data, the Main Module that runs the simulation, and the Post Processor Module that analyzes post simulation data (AFLCMC/EZJS, 2013). The software is used to simulate studies concerning Air Force base level functions (e.g. maintenance and supply) and manpower studies. This in turn, allows operators and strategic leaders to assess the availability of support resources and operational weapon systems (AFLCMC/EZJS, 2013).

The original LCOM was created in 1966 by the Air Force Logistics Command and the Rand Corporation (AFLCMC/EZJS, 2013). LCOM was initially utilized by organizations like the Tactical Air Command, the Air Force Human Resource Lab, and

the Air Force Systems Command for various studies (Erdman, 2014:6). The results of these studies provided insights to weapon system procurement and Air Force aircraft maintenance manning standards. LCOM significantly aided in exploring the trade-offs between various types of assets used for weapon systems throughout the acquisition stage (AFLCMC/EZJS, 2013). The impacts of these studies were a key contributor to the overall reduction in weapon system costs (AFLCMC/EZJS, 2013).

There have been an abundant amount of upgrades since its creation in 1966. Currently the Air Force Life Cycle Management Center (AFLCMC) operates and maintains LCOM. Their most recent update of the model was released in 2014 and known as LCOM-ATK (AFLCMC/EZJS, 2013). While the interfaces have changed, the goal and applicability of LCOM remains the same. LCOM is meant to capture logistics and provide insights of maintenance and supply to Air Force leaders (AFLCMC/EZJS, 2013).

One of the great things about this software is that it leaves a significant amount of control over the level of detail that the model environment possesses. This was vital in our research because the conflicting aggregation levels of wargames and logistic models. This was the key in choosing a logistics model as our base model as opposed to a wargame combat model. The LCOM model is designed to simulate part failures, or other similar subsystems, and process the spares to capture the support system during an engagement over a given period of time (AFLCMC/EZJS, 2013). This allows its users to tailor the model into a plethora of different types of logistics.

The Input Module decreases and reformats the data provided by users into a data structure appropriate for the Main Module (AFLCMC/EZJS, 2013). More specifically,

the Input Module gathers the parameters set by the user, constructs a flying program based in terms of sortie operations and/or activities requiring specific types of aircraft or non-aircraft resources (AFLCMC/EZJS, 2013). The Input Module simply gathers all the data created by the user, generates sorties and creates the corresponding environment used in the Main Module.

The Main Module carries out the simulations within the environment created by the user and the Input Module (AFLCMC/EZJS, 2013). The Main Module process is as follows: it begins with the sortie schedule, incorporates part failures/malfunctions based on validated and historical data, gathers necessary resources to complete the scheduled sortie, allots the time required in making scheduled or unscheduled repairs, and incorporates the exchanges of the demand process for resources (AFLCMC/EZJS, 2013). Each of these described responses is only a small portion of what LCOM truly does. The ability to describe the maintenance and support of aircrafts over multiple days, months or even years is a key factor on why the model has lasted and continues to thrive in today's every growing world.

The Post Processor Module provides users with the opportunity to conduct post-simulation analysis on the data gathered from the Main Module (AFLCMC/EZJS, 2013). The data gathered from the Main Module is large and robust because it covers an extended period in time and tracks a large volume of entities. The Post Processor Module consolidates all of these data points into various types of reports, and develops visual representations to provide further insights to its users (AFLCMC/EZJS, 2013).

The output of LCOM-ATK is consolidated into reports (AFLCMC/EZJS, 2013). The reports are groups of similar statistics or MOEs collected. For example, statistics

gathered from aircraft activities are gathered into a single report referred to as Group C (aircraft). The reports are gathered in Group A (mission), Group B (activity), Group C (aircraft), Group D (personnel), Group E (shop-repair), Group F (supply), Group G (equipment) and Group H (facility) (Erdman, 2014:28). A complete listing of the measures used for our logistic simulation is included in Appendix A of this thesis.

Summary

This chapter discussed the history of wargames and the issues associated with not incorporating logistics. The heart of the problem is the differences of fidelity between a typical wargame and logistics simulation. Wargame simulations are aggregated at the campaign level, while logistics simulations are constructed with a higher level of detail at the operational/tactical level. This difference in fidelity has been a key factor in wargames being played with the exclusion of logistics. The next chapter of this thesis describes our methodology for incorporating logistics within AF wargames.

III. Methodology

Solving how logistics can be captured during wargames requires our study to start from the beginning of wargames. We explore what wargames are and why USAF performs wargames. Once we understand the added benefits of wargames to USAF we can focus on why logistics should be incorporated. This understanding ultimately helps us shape our methodology to capture ACS capabilities and constraints in a wargame.

Wargame Overview

There is no definitive date in which wargames were created. It is due to the fact that wargames have been executed throughout the history of mankind. The definitions vary but the heart of each definition remains the same. Wargames are fictional studies carried out by military leaders to construct, amend and/or validate a war plan (Collins, 2012). There are various forms of wargames that are also carried out by the commercial industry; however, we focus on US Air Force wargames and understand the role that logistics has played in wargames. This section illustrates the shortcomings that logistics has had in wargames and the numerous issues involved with these shortcomings.

Wargames are used within several levels of the Air Force. Each level provides different types of insight, but we concentrate on Title 10 wargames. "As the Goldwater-Nichols Act of 1986 gave the service chiefs responsibility under U.S. Code Title 10 to train, man, and equip their individual forces" (Ducharme, 2012:1). The Air Force began conducting Title 10 wargames in 1995 by creating two types of wargames: Unified Engagement (UE) and Future Capabilities Game (Ducharme, 2012:2). UE wargames are completed on even years with Future Capabilities Games being held on odd years. These

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One of the main issues of UE is a failure to evaluate the logistic operations (Haffa, 2001). Logistics is regarded as an operational constraint and a failure to incorporate logistics has an impact on campaign planning (LaPlante, 1996:97). Blue Forces overestimate their effectiveness level and completely disregard the logistics involved in supporting their campaign. For example, the kill rates included in the simulations require that munitions be provided for each of the weapon systems; however, the amount of ammunition available is considered unlimited and use is not tracked (Haffa

2001). This in turn over predicts the effectiveness of US forces, under predicts the red forces, underestimates the budget, and provides less insightful results to a large number of policies and doctrine (Caffrey, 2008:37).

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LCOM-ATK Overview

In an effort to reduce cost, complexity and understanding of incorporating logistics into a wargame model, we felt that using a preexisting logistics model as the baseline would significantly reduce these three factors. We needed a logistics model that ran at the operational level and contained all of the support personnel and equipment required to capture Agile Combat Support. LCOM-ATK accomplished all of these requirements and had been used throughout the logistics community for decades.

The model constructed for this paper was developed under the Logistics Composite Model (LCOM) Analysis Toolkit (ATK) version 4.0 which is a product of

AFLCMC/EZJS with support from Frontier Technology Incorporated (FTI). LCOM-ATK is a composite of modules written in SIMSCRIPT II, which communicate with each other to function as a unit (Erdman, 2014:13). The three modules are: the Input Module that preprocesses the data, the Main Module that runs the simulation and the Post Processor Module that analyzes post simulation data (Erdman, 2014:27). The software is used to simulate studies concerning AF base level functions like maintenance and supply. LCOM relies on the fact that through the simulation, the operators can assess the availability of support resources and operational weapon systems (Erdman, 2014:11).

One of the great things about LCOM is that it leaves a significant amount of control to the user over the level of detail that the model environment possesses. This was vital in our research because of the conflicting aggregation levels of wargames and constructive logistic models used for analysis. This was the key in choosing a logistics model as our base model as opposed to a wargame model. The LCOM model is designed to process spares and other like subsystems to capture the support system during an engagement (AFLCMC/EZJS, 2013). This allows its users to tailor the model and the three modules to capture a wide range of different types of logistics processes and resources while maintaining a manageable level of understanding and complexity. The general flow for the three modules is shown in Figure 1.

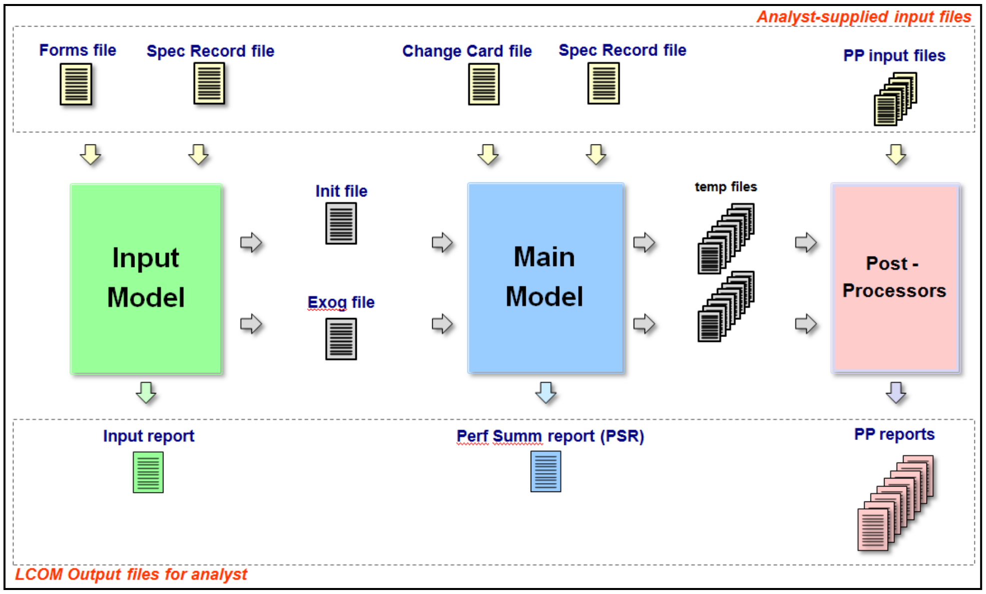


Figure 1. LCOM Process (Erdman, 2014:27)

The output of LCOM-ATK is consolidated into reports. The reports or statistics collected are broken into groups that have a varying number of measures within them (AFLCMC/EZJS, 2013). We used all of the measures described in each of the following groups in our analysis, but please note that they are only a subset of metrics available within LCOM-ATK. A complete listing of the measures used for our logistic simulation can be found in Appendix A of this paper. In addition, please note that throughout this paper measures, metrics, and statistics are equivalent.

The first set of reports is Group A or also known as Key Mission Statistics (Erdman, 2014:28). This group contains the metrics that provide a top level assessment of the missions conducted during the engagement (AFLCMC/EZJS, 2013). Metrics that deal with completing sorties, attrition, and supply wait times are found in Group A. A subset of the statistics gathered in this group is shown in Table 1.

Table 1. Group A (Walker et al., 2010)

Stat	Description
A4	Number of sorties requested
A5	Number of sorties initiated
A7	Number of Attritions
A11	Average aircraft pre-sortie maintenance (hours)
A16	Average aircraft mission wait status (hours)
A20	Average aircraft post-sortie time (hours)
A26	Number of sorties completed

The next set of statistics is Group B which encompasses all Key Activity Statistics (Erdman, 2014:28). This group contains the metrics that provide a view of all the activities that are started in the simulation (AFLCMC/EZJS, 2013). Activities encompass all the movement of entities within the simulation. Some examples of activities are: receiving engines, requesting ammunition, or time taken to receive maintenance parts. A subset of the statistics gathered in this group is shown in Table 2.

Table 2. Group B (Walker et al., 2010)

Stat	Description
B1	Number of activities requested
B2	Number of activities started
B3	Number of activities cancelled
B4	Average time to get resources (hours)
B8	Average activity length (hours)
B12	Number of activities completed
B13	Number of exogenous activities requested

Group C contains the Key Aircraft statistics (Erdman, 2014:28). This group contains the metrics that provide a view of all the activities that are associated with the aircraft within the simulation (AFLCMC/EZJS, 2013). Group C focuses on metrics such as number of aircraft available, unscheduled maintenance conducted on the aircraft, and number of sorties completed. A subset of the statistics gathered in this group is shown in Table 3.

Table 3. Group C (Walker et al., 2010)

Stat	Description
C1	Number of aircraft authorized
C2	Number of aircraft days available
C3	Percent sorties (including alert)
C4	Percent unscheduled maintenance
C5	Percent scheduled maintenance
C6	Percent NMCS
C7	Percent time waiting to fly

The Key Personnel Statistics are gathered in Group D (Erdman, 2014:28). This group contains the metrics that provide a view of all the activities that are associated with the personnel within the simulation (AFLCMC/EZJS, 2013). These statistics consider the entire maintenance population and focus on metrics incorporating the manhours used for activities. A subset of the statistics gathered in this group is shown in Table 4.

Table 4. Group D (Walker et al., 2010)

Stat	Description
D1	Manhours available
D2	Percent utilization
D3	Manhours used
D4	Percent used for unscheduled maintenance
D5	Percent used – scheduled maintenance
D8	On-equipment manhours used
D9	Off-equipment manhours used

Group E covers the Key Shop-Repair Statistics (Erdman, 2014:28). This group contains the metrics that provide a view of all the activities that are associated with shop repair within the simulation (AFLCMC/EZJS, 2013). The metrics in Group E are meant to show how well the shop is doing in repairing the aircraft. Metrics like the number of items backlogged, the repair cycle time, and number of items in repair all provide a snapshot of the repair shops. A subset of the statistics gathered in this group is shown in Table 5.

Table 5. Group E (Walker et al., 2010)

Stat	Description
E1	Number of rep gens or exog demands
E4	Average base repair cycle (days)
E10	Number of items in repair (EOP)
E11	Number of items backlogged (EOP)

The next set of statistics is Group F which contains the Key Supply Statistics (Erdman, 2014:28). This group contains the metrics that provide a view of all the activities that are associated with the supply within the simulation (AFLCMC/EZJS, 2013). The metrics in Group F are meant to show how well the supply side of logistics is performing using metrics such as the number of backorder days for a part, number of units demanded, and the number of cannibalizations. A subset of the statistics gathered in this group is shown in Table 6.

Table 6. Group F (Walker et al., 2010)

Stat	Description
F1	Authorized quantity
F3	Number of backorder days
F4	Number of units demanded
F8	Percent demands not satisfied
F9	Number of cannibalizations
F11	NMCS indicator

The Key Equipment Statistics are captured in Group G (Erdman, 2014:28). This group contains the metrics that provide a view of all the activities that are associated with the maintenance equipment within the simulation (AFLCMC/EZJS, 2013). The metrics in Group G are meant to show how well the maintenance equipment is holding up for the simulation. Are their issues with not having enough maintenance equipment to maintain the sorties being conducted? Questions like this can be answered investigating the metrics in Group G. A subset of the statistics gathered in this group is shown in Table 7.

Table 7. Group G (Walker et al., 2010)

Stat	Description
G1	Authorized quantity
G2	Equipment hours available
G6	Equipment hours used
G9	Number of backorder days
G10	Number of units demanded
G16	Percent demands not satisfied
G18	Number of units generated

The final set of metrics used for our wargame model is Group H which consists of the Key Facility Statistics (Erdman, 2014:28). This group contains the metrics that provide a view of all the activities associated with the maintenance facilities within the simulation (AFLCMC/EZJS, 2013). The metrics in Group H are meant to indicate the performance level of the maintenance facilities. Are there enough maintenance facilities for the aircraft to be repaired or are there too many maintenance facilities that are not being utilized? Questions like these can be answered with the metrics found in Group H. A subset of the statistics gathered in this group is shown in Table 8.

Table 8. Group H (Walker et al., 2010)

Stat	Description
H6	Facility hours used
H9	Number of backorder days
H16	Percent demands not satisfied
H17	Average hours used/demand
H19	Facility hours backlog (EOP)

Logistics Simulation

Capturing logistics within wargames also requires a decision of when the logistics simulation should be conducted. What are the advantages and disadvantages of running

the logistics simulation before, during, or after the wargame? In order to answer this question we first investigate what the goal of a wargame is.

As stated previously, wargames are a tool for commanders to test combat strategies and understand the capabilities of enemy forces. They are not necessarily designed to perform sensitivity analysis or optimization. The loss of not capturing logistics within wargames primarily influences Blue Force capabilities. There are various constraints that are lost when not considering logistics. For example, a Blue Force Commander might overcome an enemy by using ten F-35s; but in actuality, the air base that the F-35s originate from can only maintain and operate eight F-35s due to the amount of maintenance facilities. This example of an overestimation of Blue Force capabilities may lead to budget overruns, failing missions, loss of airmen, etc. Thus the role of logistics is to further define a near actual representation of Blue Force capabilities by providing limitations and constraints.

Now that we have defined the role of logistics within wargames, we can determine when would be the most appropriate time to run a logistics simulation. The most ideal scenario would be to incorporate a logistics simulation to inform the decisions that the Blue and Red Force commanders make during the wargame. This would provide the commanders with real time results and identify strategies that are feasible or infeasible. The down side to running the logistics simulation during the wargame is that the setup and run times for logistics models are very high. Completing a logistics simulation during an eight hour period would be highly unlikely. Thus, a metamodel would need to be constructed. This metamodel would need to reduce the amount of

variables, and in turn, provide a reasonable run time that would allow the logistics model to be completed during the wargame.

A more likely scenario would be to run the logistics simulation before or after the wargame. In both of these cases, commanders are provided with more realistic capabilities and understand the limitations of their respective forces. If the model was to be executed after the wargame, then the logistics simulation could be modified to incorporate the wargame commanders' strategies implemented during the wargame. This would allow the logistics simulation to determine the feasibility of each of their strategies. However, these feasibility results are provided after the wargame is concluded which doesn't provide commanders with the opportunity to alter their approach.

Because of this reason, we feel that the most appropriate time to capture logistics within wargames is before the wargame is played. The commanders can adjust their strategies during the wargame because they are provided with logistics limitations and constraints before the wargame begins. This is a very important benefit because this information can provide better insights from wargames. As with any case, there are always downfalls to any approach. The disadvantage for this case is that the model would not have the ability to incorporate the decisions made during the wargame. But as we stated previously, the goal of logistics being incorporated into wargames is to provide more realistic capabilities of the forces. Completing the logistics simulation before the wargame does this and provides the wargame commanders with information at an ideal moment in time. We carry this approach a step further in later discussions, developing a metamodel from our logistics simulation to be used during the wargame.

The next step after selecting when our logistics simulation would be conducted is to construct the fictional scenario our wargame would portray. The problem set forth for us through AFMC was to assist and provide insight on decisions made for the "Pivot to the Pacific." This is the idea that the US would shift its focus from the Middle East to the Pacific region. Due to security concerns, the scenario for the wargame is completely fictional. There are no real opposing forces, the flight times used to conduct sortie operations are not real, and the locations of both Blue and Red Forces do not reflect reality. The idea of our study is to provide a proof of concept that a stand-alone logistics simulation can effectively capture a more accurate representation of the impact of ACS for a standard wargame scenario in a timely manner (before or during wargame play).

The scenario takes place in the Pacific with three Blue Force units and two Red Force units. The forces are captured in LCOM-ATK by having Blue forward operating bases (FOB) each conducting sorties via F-35s over two regions controlled by the Red Forces. We constructed the model using a predefined set of Blue Force strategies to conduct air operations over a 180 day period.

The lengths of UEs are typically 4-14 days, but we selected an extended period of 180 days because logistics usually cannot be captured in a short window of time. For example, running a scenario that lasted seven days wouldn't capture logistics because the logistics operations would be near zero. The question that then arises is at what point is logistics relevant? Due to the scope and timeframe of this study, we feel that assuming 180 days would be sufficient, but further analysis could determine the actual minimum amount of time needed to capture logistics. Using this extended period of time also allows the users with the ability to extract a set of days matching the wargame length

from any point. This then could determine what effects logistics would play during the wargame and provide more accurate starting logistics capabilities. In addition, as we have seen with the wars with Iraq and Afghanistan, our future engagement planning should include a sustainment piece. Thus selecting a time period of 180 days is reasonable because it allows logistics to be captured during both a surge and sustainment window.

The three Blue FOBs each contain 24 Joint Strike Fighters (JSF), 3 maintenance facilities, 6 maintenance crew members, ammunition, fuel and a vast amount of parts to repair on the JSF. LCOM-ATK incorporates thousands of parts that can fail on the JSF, but we want to focus specifically on ACS by incorporating engine failures. The failure of missions due to unscheduled maintenance and backorder days of engine spares provides more realistic force capabilities. We want to explore questions like how many days would a JSF be unable to operate or what is the impact to day to day operations if an engine failure occurs. Tracking engine failures and spares allows us to accomplish this and provides a sufficient representation of ACS within a wargame scenario.

The Red Forces have no ability to defend against the JSF sortie operations but control two ground regions in the Pacific. Due to this aspect, Red Forces are not able to attrite Blue Forces, however, this could be easily modified within LCOM-ATK. In addition, we felt that this didn’t impact our overall goal for this thesis, which was to capture logistics in a wargame model. Figure 2 provides a visual representation of the logistic simulation scenario.

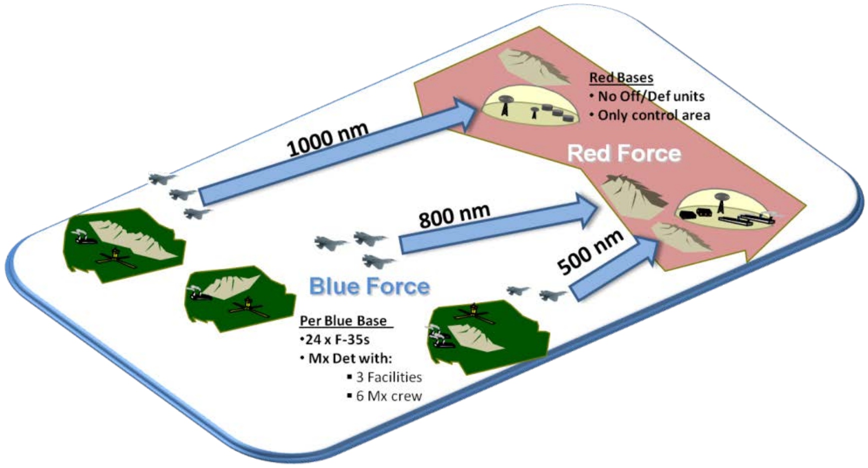


Figure 2. Wargame Scenario

A sortie completed by the Blue Force is considered successful if the JSF is able to load ammo, refuel, pass maintenance inspections, takeoff, reach the Red base, and return to the Blue base it originated from. The sortie operations vary in length based on the origin of the JSF. Figure 2 shows the distances from each of the bases, while Figure 3 captures the sortie operations modeled within LCOM-ATK. We are not concerned with the ammunition hitting the desired mark or destroying a target, but are concerned with the amount of ammunition available. Specifically, we focus on if enough ammunition is available to complete the sortie. We are not varying the types of ammunition, but LCOM-ATK can be altered to incorporate various types of ammunition. The goal of the logistic simulation for each sortie operation is to focus on the logistic support required to complete that specific mission.

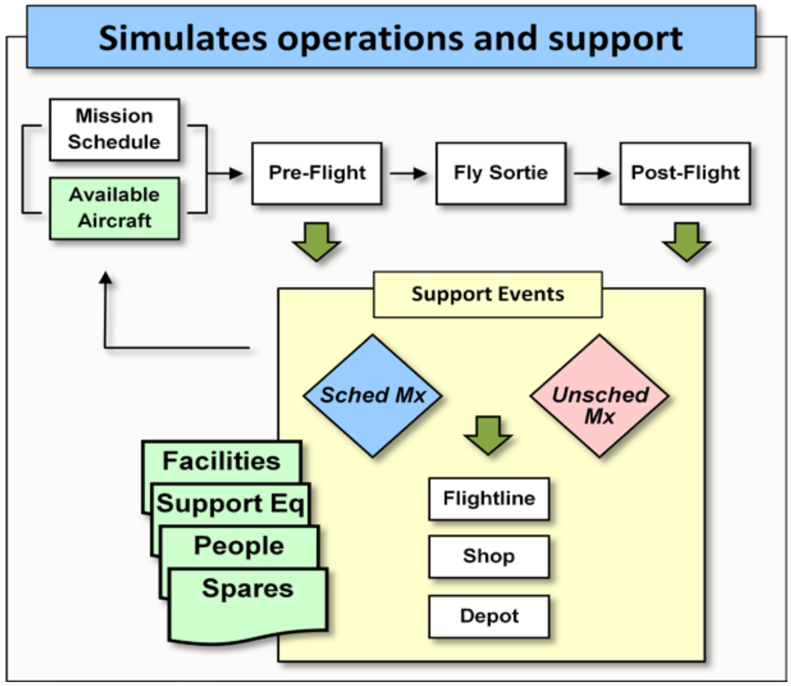


Figure 3. Simulation Model (Erdman, 2014:5)

The logistics simulation has time steps of 24 hours and a time length of 180 days. The time step is selected for 1-day intervals because that is customarily the length for logistic models and how real world metrics are gathered. We selected 10 replications because it provides a reasonable 95% half width for statistics collected.

Analysis Methodology

Logistics models typically are run at a low aggregation level and have high fidelity. What this corresponds to is an output of a large number of variables and data points. For example, our wargame scenario contained three Blue Force units and two Red Forces units with logistic support for the Blue Forces. The Blue Force had one squadron of JSFs (24 x F-35) located at each FOB with ACS. This resulted in an output of well over 100 metrics with 100,000 data points. Presenting this to a group of decision

makers within a wargame is a daunting task because you want to inform decisions without overwhelming them.

We are capturing logistics in wargames to provide more realistic force capabilities. Our analysis focuses on providing trends and limitations of the logistics simulation (e.g. sortie rates, engine failures, F-35 downtimes, scheduled maintenance, available ammunition, etc.). We showcase what ACS can provide during surge and sustainment phases of operations. These results are then provided to decision makers within wargames to understand what their force limitations are.

In addition, we explore the feasibility of developing a metamodel that can be completed during a wargame. We use various Multivariate Analysis techniques (Principal Component Analysis, Discriminant Analysis, Factor Analysis, and Artificial Neural Networks) to reduce the dimensionality while maintaining minimal loss of information. The benefits of having the ability to run logistics metamodels during wargames are immense. Commanders are given near real-time feedback on their decisions and can alter their strategies throughout the wargame.

Conclusion

The size of logistic models and the time constraints imposed during wargame play, require investigating whether there are alternative approaches to running a logistics simulation during a wargame to capture ACS within a wargame. Specifically, should the logistics model be run before, during, or after the wargame? Completing the model during the wargame is the ideal approach and is plausible, but is highly unlikely because of the time constraints and modifications to the model. A metamodel would need to be

developed that can capture ACS with a small subset of logistic inputs and allow the model to run significantly faster. The most practical approach is to complete the logistics simulation before the wargame. Completing the model at this time allows logistics considerations to be included to provide commanders with more realistic force capabilities and to gain better insights from wargames. The next chapter of this thesis analyzes these two approaches by using statistical and multivariate analysis.

IV. Analysis & Results

The analysis section for this study is broken into two sub-categories. The first sub-category focuses on gathering the output data from the logistics simulation to develop further insights for the wargame. The analysis utilizes graphs, 95% confidence intervals, and hypothesis testing to better define the effectiveness and limitations of Blue Forces. The second sub-category explores the development of a metamodel to provide a suitable logistics model to be run during the wargame. This part of our analysis uses Principal Component Analysis (PCA), Discriminant Analysis (DA), Factor Analysis (FA) and Artificial Neural Networks (ANN) on the output data from the logistics simulation to construct a metamodel.

The output data from the logistic simulation is in the form of hundreds of thousands of points with 140 MOEs. We partition the data into three groups to allow for testing and validation. We use 70% of the data to perform analysis, 15% for testing, and 15% for validation. In addition, the output data is not balanced in terms of the response variable (sortie completion or not). We achieve approximately 85% success and 15% failure rates. An unbalanced set of data affects both sub-categories of analysis, but we explicitly explain the issues that arise within the multivariate analysis discussion.

The training and testing of the data is captured using the hold-out method for cross-validation (Devijver and Kittler, 1982:10). This method breaks the data into three groups to train the predictor, test the predictor, and validate the predictor. As stated previously, we divided the output data into 70%/15%/15% for training, testing, and validation. More specifics on how we partitioned the data are discussed with our multivariate analysis.

We use all of these different types of analysis to demonstrate that incorporating logistics into wargames provide commanders with more effective insights. These insights carry over into many facets within the DoD that impact planning, development, and procurement of future weapon systems.

Statistical Analysis

A summary of the sorties completed during a single replication of the logistics simulation is provided in Figure 4. This plot showcases the sortie completion rate for each Blue base throughout the 180 day campaign. We chose to display a single replication because it shows significant differences in sortie completion rates by base. An average of the ten replications does not display this characteristic because of the randomness involved with LCOM-ATK and the fact that each replication is independent of each other. We arbitrarily chose this replication to provide insight, and it is not more significant than any of the other replications.

Figure 4. Sortie Completion Rate

The graph in Figure 4 shows that all three bases start off relatively high in their respective sortie completion percentages (90-100%), but begin to draw down throughout the campaign. Each of the Blue bases shows that they are completing approximately 85% of their missions after the 95th day. The average of the ten replications for sortie completions agreed with this finding (85% mission success rate), and achieved an average success rate of 83%. Another insight from the single replication plotted in Figure 4 is that there are spikes indicating significant drops in completing missions. These drops in the plot can come from any number of things, but a good initial area to explore is in unscheduled maintenance.

A spike might occur because of unscheduled maintenance due to engine failures or other parts needing repair on the JSF. These unscheduled events do not allow the JSF to be operationally ready, and in turn, not complete the mission. Figure 5 showcases the JSFs unscheduled maintenance rates for each Blue base throughout the 180 day campaign. Please note that Figure 5 is the unscheduled maintenance rate for the same single replication used in Figure 4.

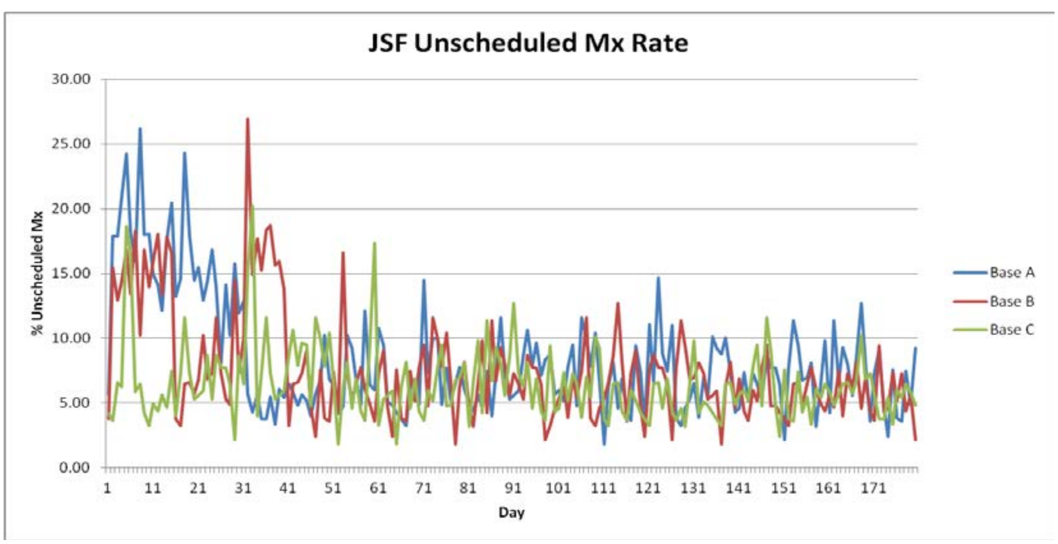


Figure 5. JSF Unscheduled Maintenance Rate

Figure 5 does have spikes that indicate a significant increase in unscheduled maintenance on the same days as the drops in sortie completion rates as shown in Figure 4. For example, on day 31 Base B completed approximately 72% of its missions that day. This was a drop of 28% in one day. Day 31 on Figure 5 shows a large increase in unscheduled maintenance for that day. Insights like this can be found looking throughout plots, but it is time consuming and difficult to provide significance and understanding of why things are occurring.

We transfer over to conducting statistical analysis on the logistics simulation output data and determine if there are added insights that can be provided to wargame commanders. Some key statistics are provided in Table 9. These statistics are gathered from the entire set of replications from the logistics simulation.

Table 9. Logistics Simulation Analysis

	Base A			Base B			Base C		
	Mean	St Dev	95%HW	Mean	St Dev	95%HW	Mean	St Dev	95%HW
Sortie Comp (%)	87.5	4.6546	2.8849	88	5.2813	3.2733	91.9	7.0658	4.3793
Sortie Comp (#)	7.4722	3.4405	2.1324	7.4836	3.3188	3.5357	7.8277	3.5357	2.1914
JSF Op Ready (%)	35.446	10.463	6.4848	37.422	10.419	6.4577	39.589	10.382	6.4346
Unsched Mx (%)	8.4	4.5018	2.7902	7.6	4.1539	2.5746	6.5	2.8659	1.7763
Sched Mx (%)	12.682	3.3517	2.0773	11.276	3.5058	2.1729	9.8136	3.4598	2.1444
Msn Wait Time (hr)	0.5675	0.0552	0.0342	0.5179	0.0665	0.0412	0.4884	0.0684	0.0424

Table 9 showcases the mean, standard deviation and 95% half width for each of the Blue bases. There is a trend with each of the MOEs displaying Base C performing better than Base B and Base A. This might occur because of the distances involved with each of the Blue bases and their Red ground area to attack. The greatest change between the Blue bases in Table 9 is the sortie completion rate. Base A was completing approximately 87.5% sorties while Base C was completing 91.9% sorties. This is

interesting because you would assume that all the bases would perform at around the same level, but the distance of sorties might be a factor in this case as well.

We conduct a hypothesis test in which our null hypothesis is that Base A has the same sortie completion rate as Base C. We use a two sample paired T-test at an alpha level of .05 with no assumptions required for the two samples variances. After performing the test, we reject the null hypothesis because our T statistic is -6.996, which is less than our T critical value of -1.968. This implies that the sortie completion rate for Base A is not equal to sortie completion rate of Base C; however, the difference in means of the two bases is low (4.4%). We investigate further by producing a 95% confidence interval (CI) on the difference of means of sortie completion rates for both Base A and C. We obtained a 95% CI of [3.1597, 5.6403] which indicates that the means are in fact not equal because the interval does not contain zero, and that Base C is better than Base A by about 5% in sortie completion rates. This insight might drive an analysis to be conducted on why is there a difference between the bases and/or determine whether a FOB should even be located in Base A.

We then conduct a hypothesis test in which our null hypothesis is that Base A has the same JSF operational rate as Base C. This metric determines how many JSF are operationally ready and can complete sortie operations on a daily basis. We use a two sample paired T-test at an alpha level of .05 with no assumption required for the two samples variances. After performing the test, we reject the null hypothesis because our T statistic is -3.77 and is less than our T critical value of -1.968. This implies that the JSF operational rate for Base A is not equal to JSF operational rate of Base C. Constructing a 95% confidence interval on the null hypothesis that the difference in means of JSF

operational ready rates is zero provides more insight. We obtained a 95% CI of [3.461, 4.8234] which indicates that the means are in fact not equal because the interval does not contain zero, and that Base C is better than Base A in JSF operationally ready rate. This insight might alter a wargame commander's strategy in not utilizing Base A as much and focus on conducting more operations with Base C.

This small subset of statistical testing demonstrates the type of information we can provide commanders during wargames to more accurately represent their forces and capabilities. For example, commanders might be conducting operations with three full JSF squadrons per day. This would result in 72 sortie operations in a day; however, if you incorporate ACS into the wargame, our logistics simulation showcased that only approximately 24 sorties can be accomplished per day. This is a very important insight because the number of JSF squadrons, ammunition, available engine spares, maintenance crew members, amount of fuel, etc. would need to be increased to maintain the Blue Force capabilities captured in the wargame. In either case, the wargame commander may alter their strategy with this more accurate information gathered from incorporating ACS capabilities.

Multivariate Analysis

The purpose of this analysis is to develop a data screening approach that results in validated predictive metamodels. We use various multivariate analysis techniques to provide decision quality information from the output data to assist the decision makers in making informed judgments in an expeditious timeframe. The goal of each of the techniques we discuss is to better understand the observations (output variables) from our

simulation and develop approaches to more efficiently and effectively use the observations in evaluating selected MOEs. We select sortie completion as the response variable for our study; however, many other MOEs are available within LCOM-ATK for a similar analysis.

The logistic simulation output database consists of 140 variables that captured ACS over 180 days in the Pacific region. The data gathered is completely fictitious, but the scenario modeled in LCOM-ATK could be quickly and easily altered to represent an actual wargame scenario.

We partition the data into three groups to allow for testing and validation. We use 70% of the data to perform analysis, 15% for testing, and 15% for validation. Each data point contains output for a single replication over 180 days. The data points are randomly selected using the Excel random function by assigning each data point a random number between 0 and 1. The top 70% are used for analysis, the next 15% for testing, and the bottom 15% for validation. We then ensure that each set of data contains approximately equal balances in terms of success and failures of the response variable (sortie completion or not). We achieve approximately 85% success and 15% failure rates for each of the sets. An unbalanced set of data may affect the multivariate analysis techniques in correctly predicting sortie completed (SC) or not (SNC). The models may tend to gravitate towards the heavier weighted response and continue to predict that response, which in turn, may skew the prediction levels. We address this issue within each of the multivariate analysis techniques.

Principal Component Analysis (PCA)

The first technique performed is Principal Component Analysis (PCA) which is a statistical method that determines which principal components are important to the observations or simulation output variables. Principal components (PC) are orthogonal transformations of given correlated variables that transform into a set of linearly uncorrelated variables (Jolliffe, 2002:11). In other words, PCA uses eigenvectors (direction of the data) and eigenvalues (variance of the data) to determine which are the highest scores. The eigenvector with the highest eigenvalue becomes a principal component (Abdi and Williams, 2010:436). Essentially, PCs are the directions of the data where there is the most amount of variance. The purpose of PCA is to reduce the dimension of the observations by identifying patterns with minimal loss of information (Jolliffe, 2002:9).

PCA was conducted on the output data with no issues encountered while performing this analysis. All variables and data points were included in the analysis. The first step in performing PCA is determining how many components should be included in the metamodel. Horn's test provides this answer and is shown in Figure 6. All Principal Component (PC) scores above the blue line pass the test and are recommended for the metamodel.

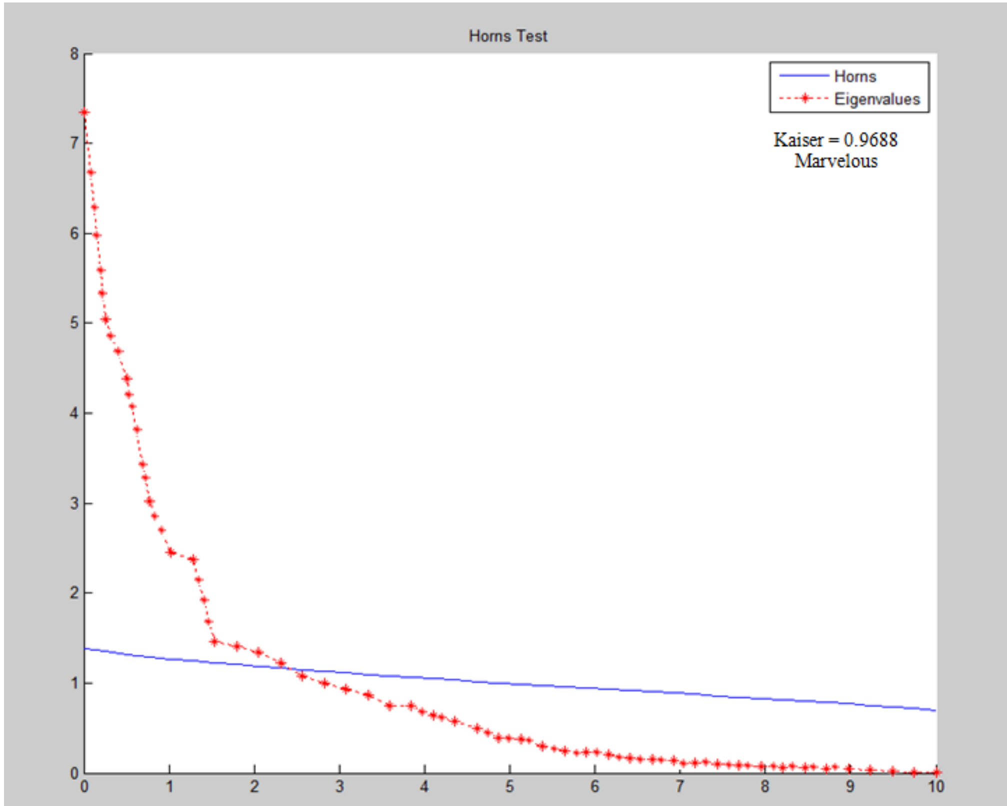


Figure 6. PCA Horn's Test

Horn's test shows that 27 PCs passed and thus we continue the analysis with this subset of PCs. In addition to this test, Kaiser's criterion was calculated and received a score of 0.9688 which is categorized as "Marvelous." To ensure a minimal loss of information, an analysis on the variance explained by the PCs is captured in Table 10.

Table 10. PCA Variance Explained

Variance Explained by PC		
	Porportion	Cumalative
PC1	0.18251	0.18251
PC2	0.08126	0.26377
PC3	0.07954	0.34331
PC4	0.07747	0.42078
PC5	0.06678	0.48756
PC6	0.05654	0.5441
PC7	0.04642	0.59052
PC8	0.04431	0.63483
PC9	0.03394	0.66877
PC10	0.03306	0.70183
PC11	0.03178	0.73361
PC12	0.02546	0.75907
PC13	0.01376	0.77283
PC14	0.01102	0.78385
PC15	0.01076	0.79461
PC16	0.01002	0.80463
PC17	0.00987	0.8145
PC18	0.00974	0.82424
PC19	0.00952	0.83376
PC20	0.00874	0.8425

As shown in Table 10, the first 16 PCs explain approximately 80% of the variability, which is an acceptable level. We then compute the loadings matrix with 16 principal components and determine which scores are the highest values in each of the respective rows. Interpreting these results provides no insight on patterns; however, we have significantly reduced the dimension size. We now move into determining if patterns are formed between SC and SNC through the various principal components.

The final step in PCA is to plot the PC loading scores amongst each other and determine if there is a set of PCs that developed patterns to distinguish between SC and SNC. Figure 7 shows the best combination of PCs with PC1 vs. PC9; however there are no clear patterns that distinguish between the two classes. These plots can distinguish sorties not completed from sorties completed but not the reverse.

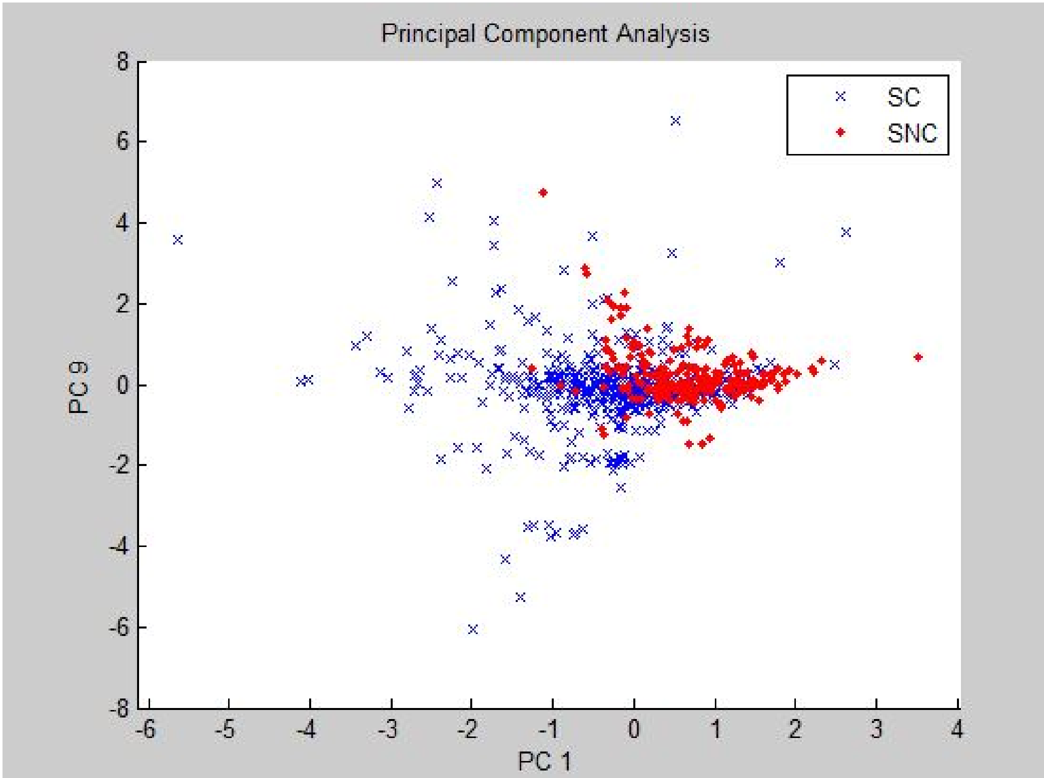


Figure 7. PC1 vs. PC9

The validation set produced the plot in Figure 8. This plot represents the same process and methodolgy that the training set underwent. The goal of the validation plot is to determine whether the patterns formed in the training set mimic the patterns formed in the validation plot.

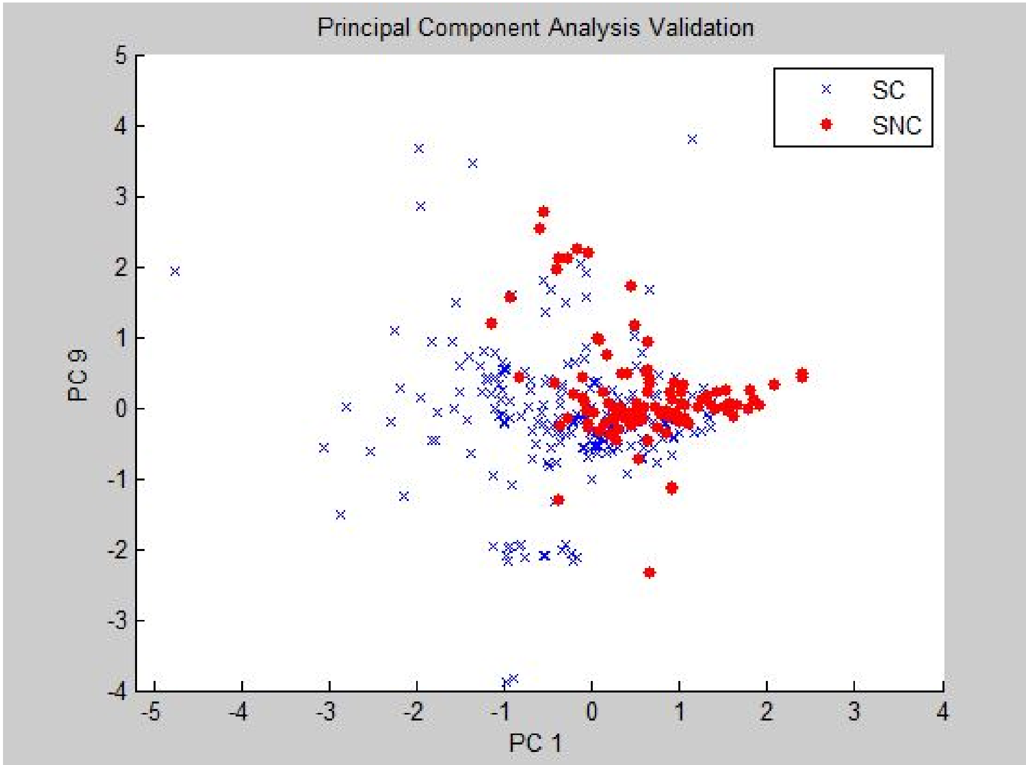


Figure 8. PC1 vs. PC9 Validation

As Figure 8 showcases, the plot matches the patterns formed in Figure 7. The plot in Figure 8 confirms that the training set analysis shown in Figure 7 is correct and validates the analysis.

In conclusion, PCA is able to reduce the dimensionality; however, it doesn't have the ability to distinguish between the two classes which results in a low overall prediction level. In addition, an interpretation of the principal components is not conclusive because of the immense amount of variables associated with each of the PCs.

Discriminant Analysis (DA)

The next analysis conducted is Discriminant Analysis (DA). DA is a statistical method to determine a categorical dependent variable, such as sortie completion, by one or more predictor variables (Johnson, 1992:39). The method begins with gathering a set

of observations, in which, the values of the interval variables are known. This produces a training set which is then used to determine whether the developed predicted model is correct (Härdle, 2007:63). The goal of DA is to decide which continuous variables discriminate between two or more groups (Johnson, 1992:45). This approach can reduce dimensionality and still maintain a high level of prediction in distinguishing if a sortie is completed or not.

In performing DA, we decided to remove all the non-continuous variables due to singularities invalidating matrix multiplication. We remove 32 variables from the analysis and continue with 108. Conducting the analysis produces the plot captured in Figure 9. This chart demonstrates the amount of variables removed and how well the model is predicting the result.

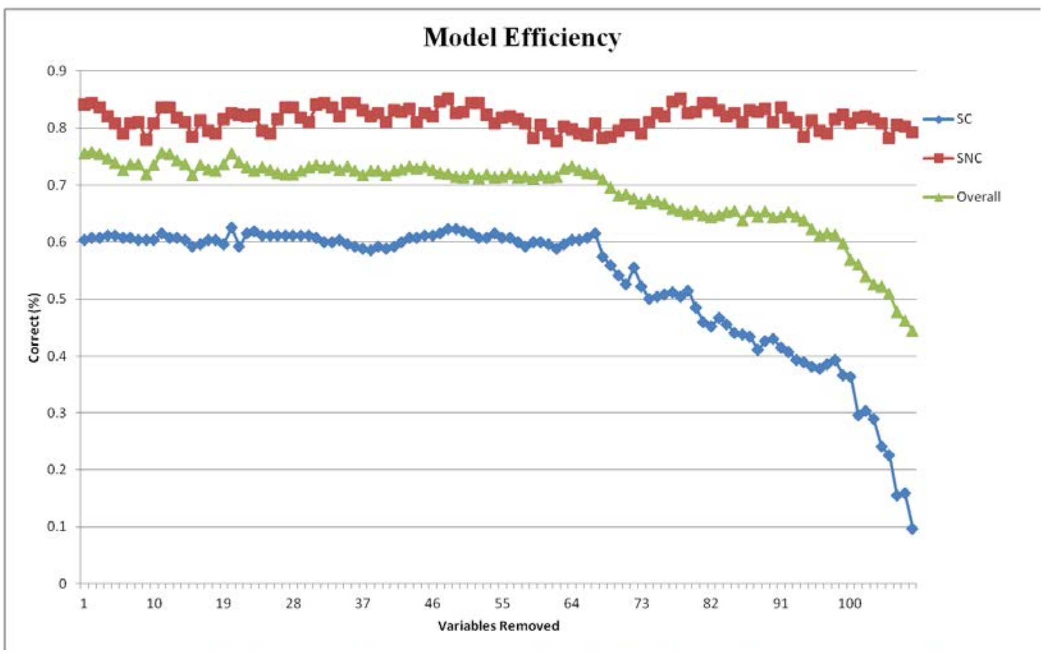


Figure 9. DA Model Efficiency

Figure 9 shows that with 67 variables removed (41 remaining), the model is able to predict approximately 61% for SC, 80% for SNC, and an overall prediction level of

70%. We believe that an overall prediction level of 75% is acceptable which occurred when 12 variables removed (96 remained). This analysis shows that it could reduce the dimensionality and continue to have a high prediction level; however, the reduction in dimensionality wasn't as far as we would have liked. We are hoping to develop a metamodel that contains less than 5 variables and maintains an accurate prediction level of no less than 75%.

Factor Analysis (FA)

The third technique used is Factor Analysis (FA). FA is a statistical method to investigate variable commonality and factor reduction (Kim, 1978: 3). FA follows the same principals as PCA, but uses a rotated loadings matrix. The purpose of FA is to reduce the number of factors and to detect relationships between factors by classifying variables (Thompson, 2004: 11). It also provides insight in grouping factors together to understand the relationship each of the factors have in the overall picture of the model (Kim, 1978: 5).

As with PCA, the same process is in place and produces the same results up until the loadings matrix. The loadings matrix for FA contains rotated data and generates alternate score referred to as Factor scores. As shown in Table 11, the Factor scores are listed in the loadings matrix and the highlighted values are the Factor scores with the maximum values in their respective rows. Please note that Table 11 contains a subset of the loadings matrix. The full loadings matrix is too large to include, but the concept remains the same for the entire matrix.

Table 11. FA Loadings Matrix

Factor Analysis Loadins Matrix										
Variable Name	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7	Factor 8	Factor 9	Factor 10
NUMBER OF MISSIONS REQUESTED	-0.87376	-0.0322	-0.20068	0.128385	0.092952	0.137436	-0.11833	-0.07903	0.074627	-0.14974
NUMBER OF MISSION ACCOMPLISHD	-0.01798	0.000921	0.001566	0.002161	-0.04955	-0.00854	-0.04046	0.048443	0.024553	0.906681
PERCENT ACCOMPLISHED	-0.01534	0.050909	0.070919	-0.07408	0.846604	0.049545	0.024848	0.052299	0.026873	0.104196
NUMBER OF SORTIES REQUESTED	-0.15806	-0.02693	-0.17084	0.84222	-0.01777	-0.12431	-0.00114	0.04269	0.258558	-0.03853
NUMBER OF SORTIES INITIATED	-0.08824	0.057075	-0.06741	0.046919	-0.0124	-0.89161	-0.00345	0.004176	0.129233	0.049135
PERCENT INITIATED	-0.25941	0.052607	0.050216	-0.01245	-0.03472	0.085072	-0.09445	0.054163	-0.04711	-0.84096
NUMBER OF ATTRITIONS	-0.37255	0.069249	-0.16634	0.157325	0.267184	0.143814	-0.55199	0.192156	-0.05367	0.428328
NUMBER OF RAM REPAIRS	-0.11119	0.043984	-0.85169	0.122003	-0.04783	0.006695	-0.04334	0.180001	-0.14612	0.097564
# OF AIR ABORTS	-0.00639	-0.06047	-0.15824	0.154436	-0.04361	0.073285	0.169765	0.666974	0.053432	0.107297
# OF SYMPATHETIC AIR ABORTS	-0.17317	-0.04281	-0.03287	0.045272	0.849451	0.016663	-0.11541	-0.09622	-0.05693	-0.04922
AVG. AC PRESORTIE MAINT.(HRS)	0.152485	-0.72978	0.048473	0.43812	-0.04979	0.248881	-0.05276	0.155454	0.203792	0.019288
MIN PRESORTIE MAINT.(HRS)	0.053753	-0.01358	-0.83348	0.185362	-0.0285	0.01394	0.000864	0.279428	-0.17135	0.01907
MAX PRESORTIE MAINT.(HRS)	-0.39165	-0.07531	-0.08866	0.098373	0.816687	-0.09056	-0.25054	-0.08336	0.01224	-0.02302
STD DEV PRESORTIE MAINT.(HRS)	-0.10007	0.070705	0.052926	0.091354	-0.04066	-0.04007	0.005346	-0.08224	0.65059	0.032405
NO. OF PRE SORTIES COMPLETED	-0.24826	-0.775	0.042625	-0.21462	0.208495	-0.00939	-0.3549	-0.00634	0.048595	-0.06792
AVG. AC MISN WAIT STATUS(HRS)	-0.89465	-0.09904	-0.2003	0.166983	0.108403	-0.1537	-0.08597	-0.03374	0.070513	-0.08038
MIN MISN WAIT STATUS(HRS)	-0.48507	0.065273	0.089642	0.638633	-0.00174	-0.20097	0.155321	0.078754	0.291334	0.002626
MAX MISN WAIT STATUS(HRS)	-0.0112	-0.79123	0.014659	0.281998	0.115033	0.231398	-0.30489	0.045106	0.190045	-0.01986
STD DEV MISN WAIT STATUS(HRS)	0.225615	-0.71571	-0.06047	0.01564	-0.25811	-0.21854	0.402526	0.190384	-0.11511	-0.06912

The next step is interpreting the Factors based on the highlighted values in each of the corresponding Factors. This is not helpful due to the immense size of the loadings matrix and was not able to produce an insightful interpretation of each of the Factors. The final step in FA is to produce plots that compare Factors amongst each other to determine if there are patterns formed to distinguish between SC and SNC. Such a plot is shown in Figure 10.

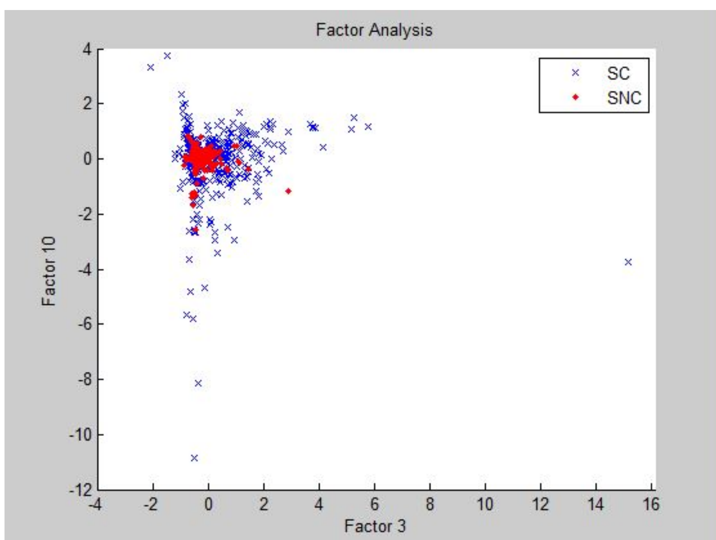


Figure 10. Factor 3 vs. Factor 10

Figure 10 shows that FA is able to distinguish SNC from SC because of the tight grouping of red; however, it is not able to distinguish SC from SNC because the red points are intertwined with the cluster of blue points.

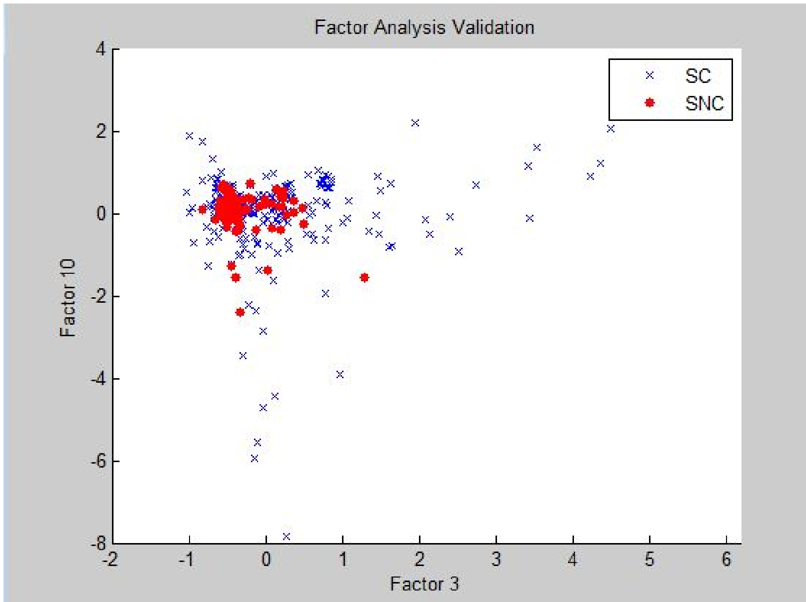


Figure 11. Factor 3 vs. Factor 10 Validation

Figure 11 is the validation plot for FA. This plot shows that it mimics the same pattern as shown in Figure 10 and thus FA is validated. However, none of the plots (including Figure 10) show any significant distinct patterns being formed. There is no clear distinction between red and blue clusters meaning that the model doesn't have the ability to distinguish between SC and SNC. We conclude that FA is able to reduce the dimensionality of the variables, but it isn't able to provide an accurate prediction level.

Artificial Neural Network (ANN)

The last analysis we perform is Artificial Neural Networks (ANN). ANN is a statistical model that estimates functions and performs pattern recognition (Schalkoff, 1997: 2). The model works such that the inputs are multiplied by weights and then computes the output of the ANN (Zurada, 1992: 36). In other words, there are nodes and

interaction of nodes referred to as connections in ANNs. The nodes are simply networks (or variables) that receive inputs and process them to yield outputs (Hagan, 1996:21). The connections of these nodes develop a global behavior that we cannot see because of the complexity and the amount of nodes (variables) (Zurada, 1992: 37). The goal of ANN is to reduce the number of variables while maintaining minimal loss of information from the given observation set (Yegnanarayana, 2009:3).

ANN is a methodology that continually removes variables from the model and outputs its prediction levels for each class (SC and SNC). We utilize ANN by eliminating the variables within a model and output its classification accuracy in a Signal to Noise Ratio (SNR) plot. This plot is found in Figure 12.

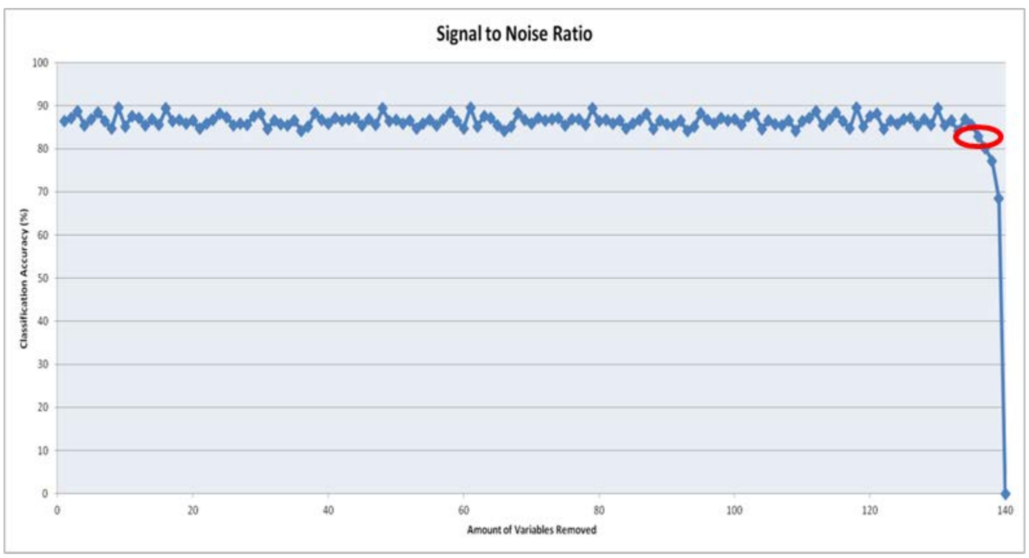


Figure 12. ANN Signal to Noise Ratio

The full model is able to predict at the 87.3% prediction level. We feel that stopping at iteration 136 (four variables remain) is acceptable because it maintains a prediction level of 85.2%. The four remaining variables are ammunition, fuel, engine spares, and maintenance crews. These variables explain the most amount of variability in

the logistics simulation model and are very promising to see. As we discussed in Chapter 2 of this paper, ACS maintains, supplies, and equips personnel and facilities. These ANN results showcase that ammunition, fuel, engine spares, and maintenance crews are key in capturing ACS through our selected MOEs. These variables could, in turn, be used to run statistical analysis before, during, or after the wargame.

To ensure that the ANN is accurate in predicting the class, we develop a confusion matrix as shown in Figure 13 where Class 1 is SC and Class 2 is SNC.

Training Confusion Matrix

Output Class \ Target Class	1	2	
1	**121254** 22.9%	**30711** 5.8%	**79.7%** 20.3%
2	**46066** 8.7%	**331993** 62.7%	**87.9%** 12.1%
	72.5% 27.5%	**91.5%** 8.5%	**85.5%** 14.5%

Validation Confusion Matrix

Output Class \ Target Class	1	2	
1	**323337** 28.5%	**10098** 8.9%	**76.3%** 23.7%
2	**10098** 8.9%	**61043** 53.8%	**85.9%** 14.1%
	76.3% 23.7%	**85.9%** 14.1%	**82.3%** 17.7%

Test Confusion Matrix

Output Class \ Target Class	1	2	
1	**40166** 35.4%	**6467** 5.7%	**86.2%** 13.8%
2	**5787** 5.1%	**61043** 53.8%	**91.4%** 8.6%
	87.5% 12.5%	**90.4%** 9.6%	**89.2%** 10.8%

All Confusion Matrix

Output Class \ Target Class	1	2	
1	**193643** 25.6%	**47654** 6.3%	**80.4%** 19.6%
2	**62026** 8.2%	**453852** 60.0%	**88.0%** 12.0%
	75.8% 24.2%	**90.6%** 9.4%	**85.6%** 14.4%

Figure 13. ANN Confusion Matrix

Figure 13 shows that the training set was able to obtain an overall prediction level of 85.5%, validation set has an 82.3% overall prediction level, testing set has an 89.2% overall prediction level and the entire set achieves an overall prediction level of 85.6%. These prediction levels all validate that the model is working effectively. The levels are

all within a reasonable distance of each other. In addition, this overall prediction level of 85.6% far exceeds our minimum requirement of obtaining a 75% prediction level.

As we stated previously, our data set is unbalanced in terms of our response variable. We didn't have a 50/50 split between SC and SNC. The result of this unbalanced set is that the ANN models make biased decisions towards the majority class (Ganganwar, 2012:1). In other words, the ANN models constructed for this paper gravitate towards predicting SC and cause the prediction levels to be skewed. The amount of skewness was not determined for our study. A reasonable assumption for the potential effect based upon the literature is on the order of 5% for each class. Further analysis could be completed to determine appropriate measures to address this issue; however, this was beyond the scope of our study. Some alternative approaches are oversampling, undersampling, adjusting the weights assigned to the classes, adjusting the decision threshold, the snowball method, and/or the *k* nearest neighbor (kNN) method (Ganganwar, 2012:2).

ANN is able to reduce the model from 140 variables to 4 variables with a prediction level of approximately 85%. The remaining variables are ammunition, fuel, engine spares and maintenance crews which are able to effectively capture ACS. These variables could be used to showcase to commanders what the limitations and constraints of ACS are within wargames. In addition, these variables are the metrics that would be used to develop a metamodel that has faster run times and the capability to provide real time logistic impact during wargames.

Summary

We provide a framework of the analysis that could be conducted before a wargame begins. We use statistical analysis with plots, paired t-tests, and confidence intervals to show that Base C was performing better than Base A in JSF operational ready rates and sortie completion rates. These two insights are then able to provide Blue commanders with the more realistic capabilities of their force. Our second analysis used multivariate analysis to reduce the number of variables and develop a metamodel. We successfully completed these two goals by using ANN and showcase that ammunition, fuel, engine spares, and maintenance crew metrics are key in capturing ACS through our selected MOEs. This is a very important finding because we can use these metrics not only in the metamodel, but also in statistical analysis. With both of these analyses, we are able to demonstrate through a proof of concept that a logistics simulation can and should be incorporated into future wargames because they provide more realistic force capabilities by capturing ACS constraints and limitations.

V. Conclusions and Recommendations

The purpose of this thesis is to gain insights on the incorporation of logistics within wargames. Including logistics provides wargames with more accurate representations of Blue Forces, and strengthens the insights gathered from wargames. Combining these two aspects allows for considerations of development, deployment, employment, and procurement of future weapon systems within the DoD.

Conclusions of Research

There have been numerous reasons why logistics have failed to be incorporated within Title 10 wargames. Wargames have been designed to test armed strategies against opposing forces over a short time window. Under this design, it has also been assumed that logistics can support any reasonable set of operations conducted during a wargame. As shown in Chapter 4, including logistics in a wargame provides commanders with a more accurate idea of forces available for combat operations. There are issues involved with maintenance, supply, and manpower that limit the number of combat sorties that can be completed on a daily basis. The bottom line is that incorporating logistics into wargames provide more realistic representation of Blue Force capabilities.

In the recent past, a separate logistics simulation has been modified and completed at the conclusion of a wargame. There has been minimal success with this approach because feasibility results are provided several days after the wargame is completed. This approach doesn't allow Blue Force commanders to alter their approach and retest their updated strategies in the wargame scenario; however, the results have shown interesting results with omitting logistics from wargames. These results have

brought greater attention to the incorporation of logistics within wargames because they have showcased that the assumption that logistics can support all operations during wargames is false. While these are great results, this still leave the fundamental issue with completing the separate logistics simulation model after the wargame has concluded.

The most ideal approach would be to modify existing wargame combat models and include logistics within them. As we discussed in Chapter 2 of this paper, this is not an easy task because of the conflicting aggregation levels between logistic simulations and combat models. This conflict comes down to a difference in metrics and processes that might not have the ability to communicate with each other within a single simulation platform. The ability to provide instantaneous results to commanders is an immense benefit though. It makes the wargame more realistic because it forces commanders to provide near real-time decisions, and in turn, provide better insights. As we discussed in Chapter 3, this still leaves the issue of long run times. Constructing a single wargame model that captures attrition, decision making, and logistics is not feasible due to these and other reasons.

The most appropriate approach would be to utilize a logistics simulation prior to a wargame. This allows for ACS to provide further representation of Blue Forces and provide more impactful insights from wargames by allowing commanders to alter their strategies during the wargame. In addition, a number of excursions could be run with the logistics simulation model to mimic possible decisions made by commanders during wargames. Ultimately, completing the logistics simulation model before a wargame provides plenty of time to modify, complete and analyze the separate logistics model.

We've discussed at what point in the process to run a logistics simulation, but we needed to also determine how we could incorporate ACS within Title 10 Wargames. We felt that using a proof of concept with a separate logistics simulation model incorporated into a wargame scenario showcased this. It demonstrated that the setup, run times and analysis could all be completed within a reasonable amount of time. It also showed that a logistics model could be tied in with a wargame by providing further interpretations of the capabilities of Blue Forces through analysis of key ACS MOEs.

We selected to use LCOM-ATK as our platform because it allows its users full control over the model constructed and captures the missions that ACS performs. We successfully developed a fictional wargame scenario in the Asia-Pacific region that has three Blue FOBs conducting operations over two Red ground areas of control over a 180 day period. The Blue offensive forces were composed of a squadron of JSF per FOB, but the main component of the model was the supply and maintenance of the JSF. Wargames have used aggregated forces such as a full squadron of JSF to be used against enemy forces, but we want to show that ACS can only operate and maintain a portion of that squadron a day.

The analysis of the output of the logistics simulation was partitioned into two cases. The first case focused on analyzing the data prior to the wargame. We used plots, 95% confidence intervals, and hypothesis tests to provide Blue Force commanders with more realistic representations of their forces. Our analysis showed that the average number of sorties that could be completed per day was 8 sorties, and that ACS could operate and maintain 30% of the JSF squadron. This is a key insight because wargame commanders should recognize some level of degraded operational capability. Insights

like this drive many factors within the DoD. This forces decision makers to determine matters such as procuring more units of an aircraft and/or funding for more personnel in AFMC to operate and maintain a larger amount of sorties.

The second case for our analysis was to complete Multivariate Analysis techniques on the logistics output data. This type of analysis was used to determine key ACS factors and reduce the dimensionality of logistics models. We used the 70/15/15 rule in regards to analyzing, testing and validating the data. PCA, FA and DA were all able to reduce the dimensionality of the logistics model but the reduction was not enough. ANN was able to produce a metamodel by reducing the dimensionality of the logistics model to four variables while obtaining a prediction level of 85% for correctly classifying a sortie as being completed or not. More importantly, the four variables that remained were ammunition, fuel, engine spares, and maintenance crews that showcase ACS can be captured and communicated to commanders using a minimal subset of factors. Essentially, these four ACS inputs can accurately predict force capabilities. We picked sorties completed (SC) or not (SNC) as our response variable, but we could use this same approach for other factors. Our metamodel, in this case an ANN, has significantly lower run times and the ability to accurately predict Blue Force capabilities utilizing the four ACS factors. This ANN is designed to be run at the end of a wargame move to provide commanders a more realistic picture of the force capabilities available for the next move.

Incorporating logistics into wargames is not an easy task. Approaching the problem by capturing logistics processes in combat models is not feasible because there are too many issues with conflicting aggregations levels to proceed with this approach. As we showcased in this paper, utilizing a verified, validated and accredited logistics

simulation model is the most practical approach. It allows ACS to further describe Blue Forces by inputting their limitations and constraints within the stochastic logistics simulation model. Using various analytical techniques, we were able to show that ammunition, fuel, engine spares, and maintenance crews are very important in describing ACS. These metrics have the ability to predict and provide commanders with meaningful results. In the end, wargames must evolve once again, and incorporate logistics within them. This evolution ensures commanders are given insights that continue to maintain the United States Air Force's (USAF) dominance in air, space, and cyberspace.

Recommendations for Future Research

This thesis provides opportunities for future work within wargames and logistics. The lessons learned throughout the process of developing a proof of concept showcased various areas that need further development.

Analyzing/Prolonging Wargames

The individuals that have designed wargames throughout the years have constructed them such that they are meant to test and develop combat strategies over a short time window. There has been little, if any, analysis on longer duration wargames in Unified Engagements. With today's ever increasing constrained budget, wargames can provide a tool in which senior leaders exercise and evaluate combat operations over a longer period in time. This would allow analysts to better determine the costs and resources associated with a sustained engagement. An approach that could be utilized for this would be to add extra time at the end of standard wargames to consider longer term engagement. This approach would allow for further analysis and a better representation

of readiness levels and force capabilities after initial surge. We recommend performing an analysis on the methodology and length that wargames currently use.

When Logistics Impacts

We arrived at a question of when does logistics impact a mission. We came to our conclusion that 180 days is sufficient because it allows for operations to carry out and for parts to begin to fail. Performing a model with too few days doesn't allow for processes to breakdown nor be impactful. We recommend performing an analysis on determining what the minimum, average and maximum amount of time required to capture logistics within simulations.

Appendix A: Measures of Effectiveness

A1 NUMBER OF MISSIONS REQUESTED	A20 AVG. AC POST SORTIE TIME(HRS)	B1 NO. OF ACTIVITIES REQUESTED
A2 NUMBER OF MISSION ACCOMPLISHD	A21 MIN POST SORTIE TIME(HRS)	B2 NO. OF ACTIVITIES STARTED
A3 PERCENT ACCOMPLISHED	A22 MAX POST SORTIE TIME(HRS)	B3 NO. OF ACTIVITIES CANCELLED
A4 NUMBER OF SORTIES REQUESTED	A23 STD DEV POST SORTIE TIME(HRS)	B4 AVG TIME TO GET RESOURCE(HRS)
A5 NUMBER OF SORTIES INITIATED	A24 NO. OF POST SORTIES COMPLETED	B5 MIN TIME TO GET RESOURCE(HRS)
A6 PERCENT INITIATED	A25 NO. OF PLUGGED SORTIES	B6 MAX TIME TO GET RESOURCE(HRS)
A7 NUMBER OF ATTRITIONS	A26 NUMBER OF SORTIES COMPLETED	B7 STD DEV TO GET RESOURCE(HRS)
A8 NUMBER OF RAM REPAIRS	A27 AVG SORTIE LENGTH (HRS)	B8 AVG. ACTIVITY LENGTH (HRS)
A9 # OF AIR ABORTS	A28 MIN SORTIE LENGTH (HRS)	B9 MIN. ACTIVITY LENGTH (HRS)
A10 # OF SYMPATHETIC AIR ABORTS	A29 MAX SORTIE LENGTH (HRS)	B10 MAX. ACTIVITY LENGTH (HRS)
A11 AVG. AC PRESORTIE MAINT.(HRS)	A30 STD DEV SORTIE LENGTH (HRS)	B11 STD DEV ACTIVITY LENGTH (HRS)
A12 MIN PRESORTIE MAINT.(HRS)	A31 AC WHICH WENT INTO MISN WAIT	B12 NO. OF ACTIVITIES COMPLETED
A13 MAX PRESORTIE MAINT.(HRS)	A32 # OF FWR MISSIONS REQUESTED	B13 # EXOG ACTIVITIES REQUESTED
A14 STD DEV PRESORTIE MAINT.(HRS)	A33 # OF FWR MISSIONS ACCOMPLISHD	B14 NO. ACTIVITIES MIN CANCELLED
A15 NO. OF PRE SORTIES COMPLETED	A34 # OF FWR SORTIES REQUESTED	C1 NUMBER OF AIRCRAFT AUTH.(EOP)
A16 AVG. AC MISN WAIT STATUS(HRS)	A35 # OF FWR SORTIES INITIATED	C2 NUMBER OF AIRCRAFT-DAYS AVAIL
A17 MIN MISN WAIT STATUS(HRS)	A36 # OF ENGINE FAILURES	C3 PCT SORTIES(INCL ALERT)
A18 MAX MISN WAIT STATUS(HRS)	A35 # OF FUEL	C4 PCT UNSCHED MAINTENANCE
A19 STD DEV MISN WAIT STATUS(HRS)	A35 # OF AMMUNITION	C5 PCT SCHED MAINTENANCE

C6 PCT NMCS	C25 %NOT MISSION CAPABLE/NMC RATE	D19 DEPRECATED STAT
C7 PCT TIME WAITING TO FLY	D1 MANHOURS AVAILABLE	D20 NMCM INDICATOR
C8 PCT TIME WAIT RESOURCES	D2 PERCENT UTILIZATION	E1 NO. OF REP GENS OR EXOG DMDS
C9 PCT OPERATIONALLY READY	D3 MANHOURS USED	E2 PCT BASE REPAIR
C10 AVG. AC POST SORTIE TIME(HRS)	D4 PCT USED - UNSCHED MAINT	E3 PCT DEPOT REPAIR
C11 MIN. AC POST SORTIE TIME(HRS)	D5 PCT USED - SCHED MAINT	E4 AVG. BASE REPAIR CYCLE (DAYS)
C12 MAX. AC POST SORTIE TIME(HRS)	D6 PCT USED AS A PRIME	E5 MIN. BASE REPAIR CYCLE (DAYS)
C13 STD DEV POST SORTIE TIME(HRS)	D7 PCT USED AS A SUBSTITUTE	E6 MAX. BASE REPAIR CYCLE (DAYS)
C14 REQUESTED SORTIES/ AC /DAY	D8 ON-EQUIP MAN-HOURS USED	E7 STD DEV BASE REPAIR CYCLE
C15 ACHIEVED SORTIES/ AC /DAY	D9 OFF-EQUIP MAN-HOURS USED	E8 PCT TIME ACTIVE REPAIR
C16 FLYING HOURS	D10 NUMBER OF MEN DEMANDED	E9 PCT TIME WAIT RESOURCES
C17 AVG. FLYING HOURS / AC / DAY	D11 NO. OF MEN DEMANDED POST SCAN	E10 NO. OF ITEMS IN REPAIR (EOP)
C18 AVG. AC PRE SORTIE TIME (HRS)	D12 PCT PROV. BY ONHAND BAL.	E11 NO. OF ITEMS BACKLOGGED (EOP)
C19 MIN. AC PRE SORTIE TIME (HRS)	D13 PCT PROV. BY GEN SUBS	F1 AUTHORIZED QUANTITY
C20 MAX. AC PRE SORTIE TIME (HRS)	D14 PCT PROV. BY EXPEDITE	F2 PCT PROV. BY PRIME ONHAND BAL
C21 STD DEV PRE SORTIE TIME (HRS)	D15 PCT PROV. BY PREEMPTION	F3 NUMBER OF BACKORDER-DAYS
C22 NO. OF PRE SORTIES COMPLETED	D16 PCT DEMANDS NOT SATIS.	F4 NUMBER OF UNITS DEMANDED
C23 NO. OF POST SORTIES COMPLETED	D17 OVERTIME MANHOURS USED	F5 PCT PROV. PRIME OR SUBS
C24 %MISSION CAPABLE/MC RATE	D18 SIMULATED MH PER FLYING HOUR	F6 PCT PROV. BY EXPEDITE

F7	PCT PROV. BY PREEMPTION	G13	PCT PROV. BY GEN SUBS
F8	PCT DEMANDS NOT SATIS.	G14	PCT PROV. BY EXPEDITE
F9	NUMBER OF CANNIBALIZATIONS	G15	PCT PROV. BY PREEMPTION
F10	NO. ITEMS ON BACKORDER (EOP)	G16	PCT DEMANDS NOT SATIS.
F11	NMCS INDICATOR	G17	EQUIP HOURS BACKLOG (EOP)
F12	NUMBER OF ORDERS	G18	NUMBER OF UNITS GENERATED
F13	NUMBER OF TURN-INS	G19	NO. ITEMS ON BACKORDER (EOP)
G1	AUTHORIZED QUANTITY	H6	FACILITY HOURS USED
G2	EQUIPMENT HOURS AVAIL.	H9	# OF BACKORDER DAYS
G3	PCT USED - UNSCHED MAINT	H16	% DEMANDS NOT SATISFIED
G4	PCT USED - SCHED MAINT	H17	AVERAGE HOURS USED/DEMAND
G5	PCT AVAIL - UNUSED	H19	FACILITY HOURS BACKLOG (EOP)
G6	EQUIPMENT HOURS USED		
G7	PCT USED AS A PRIME		
G8	PCT USED AS A SUBSTITUTE		
G9	NUMBER OF BACKORDER-DAYS		
G10	NUMBER OF UNITS DEMANDED		
G11	NO. UNITS DEMANDED POST SCAN		
G12	PCT PROV. BY ONHAND BAL		

Appendix B: Multivariate Analysis Code

```
%PCA & FA Train Final
clc
clear all
close all

%load data
PCATrain = xlsread('test.xls');
%Indicator variable
load result.mat

%Correlation matrix
cMat = corr(PCATrain(1:738,1:41));

%Eigenvalues and Eigenvectors
[V,D] = eig(cMat);

%Sort eigenvalues
D = sort(diag(D),'descend');

%Horn's curve
% horn = xlsread('FinalHorns.xls');
% figure
% hold on
% x = linspace(0,10,40);
% plot(x,horn,'b',x,D,':r*')
% title('Horns Test')
% legend('Horns','Eigenvalues')

%Variance Explained
OneVec = D(1,1)/sum(D);
TwoVec = D(2,1)/sum(D);
cumTwo = OneVec + TwoVec;
ThrVec = D(3,1)/sum(D);
cumThr = OneVec + TwoVec + ThrVec;
FourVec = D(4,1)/sum(D);
cumFour = OneVec + TwoVec + ThrVec + FourVec;
FiveVec = D(5,1)/sum(D);
cumFive = OneVec + TwoVec + ThrVec + FourVec + FiveVec;
SixVec = D(6,1)/sum(D);
cumSix = OneVec + TwoVec + ThrVec + FourVec + FiveVec + SixVec;
SevVec = D(7,1)/sum(D);
cumSev = OneVec + TwoVec + ThrVec + FourVec + FiveVec + SixVec +
SevVec;
EigVec = D(8,1)/sum(D);
cumEig = OneVec + TwoVec + ThrVec + FourVec + FiveVec + SixVec + SevVec
+ EigVec;
NineVec = D(9,1)/sum(D);
cumNin = OneVec + TwoVec + ThrVec + FourVec + FiveVec + SixVec + SevVec
+ EigVec + NineVec;
TenVec = D(10,1)/sum(D);
```

```
cumTen = OneVec + TwoVec + ThrVec + FourVec + FiveVec + SixVec + SevVec
+ EigVec + NineVec + TenVec;

%Training Scores
stdMat = zscore(PCATrain(1:738,1:41));
%Load matrix
PCALoadMat = V*sqrt(diag(D));
FALoadmat = rotatefactors(PCALoadMat(:,1:10));
%Scores matrix
FAscoresMat = stdMat * inv(cMat) * FALoadmat;
PCAscoresMat = stdMat * inv(cMat) * PCALoadMat(:,1:10);

%Validation Scores
stdValMat = zscore(PCATrain(739:1055,1:41));
%Load matrix
PCALoadMat = V*sqrt(diag(D));
FALoadmat = rotatefactors(PCALoadMat(:,1:10));
%Scores matrix
FAValdscoresMat = stdValMat * inv(cMat) * FALoadmat;
PCAValdscoresMat = stdValMat * inv(cMat) * PCALoadMat(:,1:10);

%Kaiser index
[ifs2]= IFS2(FALoadmat);
ifsFA=sqrt(ifs2)
[ifs2]= IFS2(PCALoadMat);
ifsPCA=sqrt(ifs2)

%PCA Training Plots
for i=1:10
for j=i+1:10
figure

gscatter(PCAscoresMat(:,i),PCAscoresMat(:,j),result(1:738,1),'br','x.')
    legend('SC','SNC')
    title('Principal Component Analysis')
    strName=sprintf('PC %d',i);
    xlabel(strName)
    strName2=sprintf('PC %g',j);
    ylabel(strName2)
end
end

%FA Training Plots
for i=1:10
for j=i+1:10
figure

gscatter(FAscoresMat(:,i),FAscoresMat(:,j),result(1:738,1),'br','x.')
    legend('SC','SNC')
    title('Factor Analysis')
    strName=sprintf('Factor %d',i);
    xlabel(strName)
    strName2=sprintf('Factor %g',j);
    ylabel(strName2)
```

```
end
end

%PCA Validation Plots
 for i=1:10
for j=i+1:10
figure

gscatter(PCAValdscoresMat(:,i),PCAValdscoresMat(:,j),result(739:1055,1)
,'br','x.')
    legend('SC','SNC')
    title('Principal Component Analysis Validation')
    strName=sprintf('PC %d',i);
    xlabel(strName)
    strName2=sprintf('PC %g',j);
    ylabel(strName2)
end
 end

% FA Validation Plots
for i=1:10
for j=i+1:10
figure

gscatter(FAValdscoresMat(:,i),FAValdscoresMat(:,j),result(739:1055,1),'
br','x.')
    legend('SC','SNC')
    title('Factor Analysis Validation')
    strName=sprintf('Factor %d',i);
    xlabel(strName)
    strName2=sprintf('Factor %g',j);
    ylabel(strName2)
end
end

%DA
clc
clear all
close all

%load data
DATrain = xlsread('DATrain.xls');
LCOMData = DATrain;
outMat = LCOMData(:,1:41);

%1
SC=LCOMData(1:1254,1:141);
SNC=LCOMData(255:end,1:141);
cov_SC=cov(SC);
cov_SNC=cov(SNC);
mean_SC=mean(SC);
mean_SNC=mean(SNC);
prior_SC=254/17652;
prior_SNC=498/17652;
```

```
diq_SC=zeros(752,1);
diq_SNC=zeros(752,1);
y=zeros(752,1);
for i = 1:17652
diq_SC(i)=-.5*log(det(cov_SC))-.5*(outMat(i,1:41)-
mean_SC)*inv(cov_SC)*(outMat(i,1:41)-mean_SC)'+log(prior_SC);
diq_SNC(i)=-.5*log(det(cov_SNC))-.5*(outMat(i,1:41)-
mean_SNC)*inv(cov_SNC)*(outMat(i,1:41)-mean_SNC)'+log(prior_SNC);
if diq_SC(i)>diq_SNC(i)
    y(i)=1;
end
end
class=[diq_SC diq_SNC y];
correct1=sum(y(1:12654));
wrong2=sum(y(255:17652));
confusion_1=[correct1 1265-correct1;wrong2 17862-wrong2]

test_with=zeros(2,1);
test_without=zeros(2,1);
test_result=zeros(2,1);
for i = 1:2
   test_with(i)=-.5*log(det(cov_SC))-.5*(outMat(i,1:141)-
mean_SC)*inv(cov_SC)*(outMat(i,1:141)-mean_SC)'+log(prior_SC);
   test_without(i)=-.5*log(det(cov_SNC))-.5*(outMat(i,1:141)-
mean_SNC)*inv(cov_SNC)*(outMat(i,1:141)-mean_SNC)'+log(prior_SNC);

if test_with(i)>test_without(i)
    test_result(i)=1;
end
end
[test_with test_without test_result]

temp=corr([LCOMData(:,1:141) max(diq_SC,diq_SNC)]);
loadings1=temp(end,1:141)'
[~,ind]=min(abs(loadings1));
LCOMData(:,ind)=[];
GM(:,ind)=[];

%ANN
%load data

LCOM = xlsread('test.xls')

post =1;

if post == 0
    %noise generator
    x = rand(17642,1);

    %create data matrix
    temp = [x LCOM(:,1:141)];
    data = temp(:,[1 2]);
```

```
    %std data
    input = zscore(data);

    %create output matrix
    ouput = [LCOM(:,142),1 - LCOM(:,142)];

else

    snr=[];

    wts=net.IW{1,1};

    dim=size(wts);

    noise=wts(:,1)'*wts(:,1);

    for j=2:dim(2)

        snr(j)=10*log10((wts(:,j)'*wts(:,j))/noise)

    end

end

%ANN NPRScript
clear all
close all
count=1;
load('cleandata')
load('label_proj')
data=cleandata;
output=data(:,1);
data(:,1)=[];
input=zscore(data);
permmat=[];

while count < 2

inputs = input';
targets = output';

% Create a Pattern Recognition Network
hiddenLayerSize = 141;
net = patternnet(hiddenLayerSize);


% Setup Division of Data for Training, Validation, Testing
net.divideParam.trainRatio = 70/100;
net.divideParam.valRatio = 15/100;
net.divideParam.testRatio = 15/100;
```

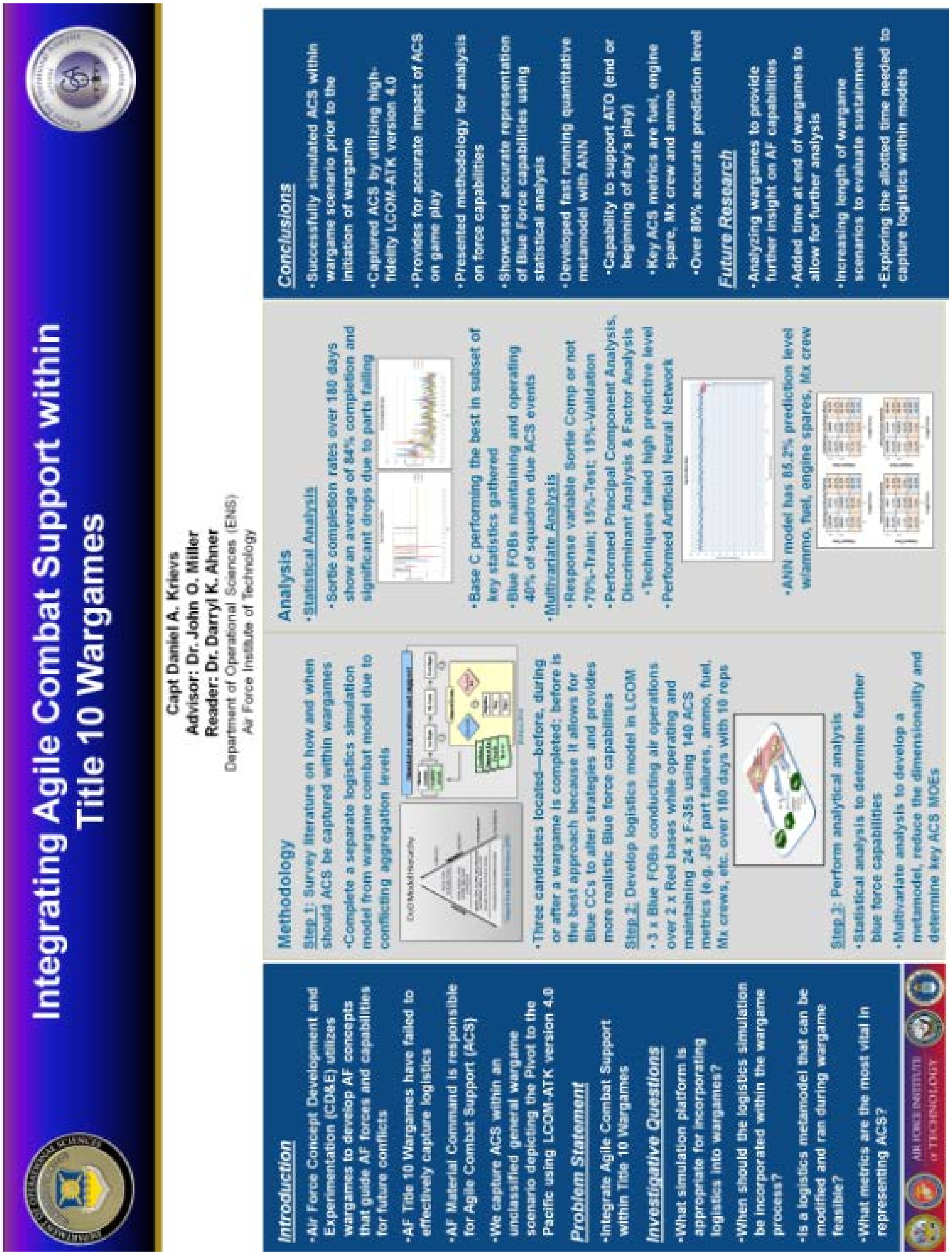
```
% Train the Network
[net,tr] = train(net,inputs,targets);

% Test the Network
outputs = net(inputs);
errors = gsubtract(targets,outputs);
performance = perform(net,targets,outputs)
permmat=[permmat performance];
figure
plotconfusion(targets,outputs)
trainTargets = targets .* tr.trainMask{1};
valTargets = targets  .* tr.valMask{1};
testTargets = targets  .* tr.testMask{1};
trainPerformance = perform(net,trainTargets,outputs)
valPerformance = perform(net,valTargets,outputs)
testPerformance = perform(net,testTargets,outputs)


snr=[];
wts=net.IW{1,1};
dim=size(wts);
noise=wts(:,1)'*wts(:,1);
for j=2:dim(2)
    snr(j)=10*log10((wts(:,j)'*wts(:,j))/noise);
end

snr
[val ind]=min(snr(2:end));
minind=ind+1
input(:,minind)=[];
count=count+1;
end
```

Appendix C: Quad Chart



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14. ABSTRACT Air Force (AF) Concept Development and Experimentation (CD&E) continually progresses the evolution of AF while achieving national security and military objectives. CD&E experiments on future challenges, procurement of new weapon systems and tests existing/innovative strategies as potential solutions. The primary tool that CD&E utilizes in conducting these experiments is wargaming. This thesis provides a foundation to incorporate logistics into Air Force Title 10 wargames. More specifically, we capture Air Force Materiel Command's (AFMC) Agile Combat Support (ACS) within an unclassified general wargame scenario. Logistics has been omitted from wargames for a multitude of reasons throughout the years. We develop a logistics simulation model of a simplified wargame scenario designed to be run within the Logistics Composite Model (LCOM) Analysis Toolkit (ATK) version 4.0 before a wargame initiates. We capture ACS within the stochastic simulation by incorporating engine failures, maintenance crews, ammunition, fuel, and various other logistics metrics. By varying the types of sortie operations and the logistics support available, further insight is gathered on Blue Force capabilities. We develop decision quality information to present to a decision maker by combining statistical and multivariate analysis. Our approach showcases how to gather insights from ACS metrics, including development of a metamodel using only four metrics to successfully predict key ACS Measures of Effectiveness (MOEs). Ultimately, we design, analyze and demonstrate that logistics can and should be incorporated into wargames.					
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